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Behavioral and neuroscientific essays on decision-making under uncertainty

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Behavioral and neuroscientific essays on decision-making under uncertainty

Gedrags- en neurowetenschappelijke inzichten ten aanzien van onzekere keuzes

Proefschrift
ter verkrijging van de graad van doctor
aan de Radboud Universiteit Nijmegen
op gezag van de rector magnificus prof. dr. Han van Krieken,
volgens besluit van het college van decanen
in het openbaar te verdedigen op maandag 4 juli
om 16.30 uur precies

door

Kim Fairley

geboren op 24 juni 1985
te Malden.

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Voor Nikki en Jessie

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Yesssss, finally, I can write as enthusiastically as I please! I can use words like ***awesome***, ***super freakin' amazing*** and **wowie** throughout this section of my thesis. And, boy oh boy, I won't be held back here!

Why am I so happy about this? Well, I should make one confession here. Namely, there is this thing you really ought to know about my PhD process…. My dearest Professors have tried their best to downscale my research texts for academic publication purposes. Words like awesome, hugely, exactly the same, basically all superlatives were banned from my papers. 'Kim, you are not writing a blog, you have to write a factual academic paper, stick to your words!'. I was very disappointed to water down my findings, I'm just a very excited girl who loves to write about, what I believe are, very exciting results, HA! But I listened, I obeyed and I learned so much about academic writing throughout this process.

But this section of the thesis is my tiny piece of overly excited Kim. And here I go!

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Chapter 1

Introduction

From my own personal experience, I can tell you that many uncertainties come together in the process of preparing to emigrate for a postdoctoral position abroad. While writing the introduction of this thesis, I experienced uncertainty in a way that almost perfectly illustrates one of the main topics addressed in this thesis.

After I had found myself a nice place to stay in my future hometown abroad, my landlord requested that I transfer a deposit. As her[1] bank account in The United States was not yet compatible with the European system, an international wire transfer was not possible. We both agreed that Western Union would be the best method to transfer the money. At the Western Union office, the lady behind the counter nicely helped me set up the process, but just before I was to sign the financial document, she politely asked what the purpose was of this transaction. She nodded while I enthusiastically explained my plans. She then looked at me seriously and told me that many scams occur with these kinds of transactions. She explained that people portray themselves as landlords and send pictures of imaginary rental properties. When I told her I was very confident that everything was fine, she continued to express her concerns. She told me that she often feels sorry for the customers that fall prey to financial scams, and she urged me to re-check all the detals of my future landlord's contact information.

Suddenly I found myself in a very puzzled state of mind. My brain was turning circles as I tried to uncover possible complot theories. Could I trust this person on the other side of the Atlantic Ocean? Was she really renting a house or trying to rip me off?

[1] As my landlord is a woman, I correctly refer to 'her' here. Nonetheless, in this thesis I will use 'she' and 'her' to refer to persons, which could equally be replaced by 'he' and 'his' otherwise.

1.1 Sources and types of uncertainty

Sources of uncertainty: As in the example above, decision-making under uncertainty (DMUU) is an inevitable feature of our daily lives. Traditionally, humans' preferences for uncertainty are measured with standard lottery elicitation methods (Charness et al., 2013). In contrast, the personal example above highlights strategic uncertainty whereby the *source of uncertainty* stems from the actions and behavior of another person (Houser et al., 2010). Generally, it is assumed that preferences for uncertainty are consistent across several decision domains (Dohmen et al., 2011; Vieider et al., 2014). Also, standard economic models assume that once a probability is fixed, or a belief is formed, it should not matter where the uncertainty stems from (von Neumann and Morgenstern, 1944; Savage, 1954). However, many experimental studies cannot find a relationship between preferences for uncertainty - measured via lotteries -and uncertainty that stems from another decision-maker (Eckel and Wilson, 2004; Ashraf et al., 2006; Ben-Ner and Halldorsson, 2010; Houser et al., 2010; and Etang et al., 2011). In this thesis I consider the role of different sources of uncertainty on DMUU and particularly focus on the role of social versus non-social sources of uncertainty.

Besides sources of uncertainty, we can distinguish between *types of uncertainty* as well (Knight, 1921). For some events we may have information regarding the likelihood of each possible outcome - as in a fair coin toss. However, for most real-life events we do not know the probability of each possible outcome (Post et al., 2008). The former is known as risk (known probabilities), whereas the latter illustrates ambiguity (unknown probabilities). Both probabilistic characteristics are captured by the general term uncertainty. We speak of risk, as a special limiting case of uncertainty (Wakker, 2010). Although most events in our daily lives are ambiguous rather than risky, empirical studies mostly address risk preferences in relation to real-life decision-making (Trautmann and van de Kuilen, 2013). In this thesis I will examine the external validity of types of uncertainty by relating both individuals' risk and ambiguity preferences to real-life decision-making.

Types of uncertainty have received much attention since Ellsberg published his findings in 1961 (BOX 1), which showed that many people are ambiguity averse. Ellsberg's finding impies a revealed preference for risky over ambiguous choice events, and contradicts subjective expected utility (SEU) (Trautmann and van de Kuilen, 2013).

Ellsberg's result paved the way for two distinct research streams, the first of which was based on theoretical models that incorporated parameters for ambiguity aversion instead of assuming maximization of SEU (Kocher et al., 2015). Such models, for instance, can explain low participation in the stock market (Easley and O'Hara, 2009; Guidolin and Rinaldi, 2009), less risky stock portfolio choices (Uppal and Wang, 2003; Liu, 2011) and suboptimal insurance choices (Alary et al., 2013; Snow, 2011). Although ambiguity has been theoretically linked to several behavioral phenomena, few empirical studies have validated the relationship between ambiguity preferences and real-life decision-making (Trautmann and van de Kuilen, 2013). Instead, individual's risk preferences have been empirically related to a diverse set of decision domains in real life (Dohmen et al., 2011; Vieider et al., 2014).

The second research stream which stemmed from Ellsberg's finding was experimental research on risk and ambiguity aversion. Based on these experimental findings, we know that people can express heterogeneous attitudes toward risk and ambiguity (Tversky and Kahneman, 1992; Wakker, 2010). Namely, preferences for uncertainty are influenced when people face losses instead of gains or when different likelihoods are considered (Kocher et al., 2015; Vieider et al., 2012; Abdellaoui et al., 2011; Dimmock et al., 2015a, 2015b; Trautmann and Wakker 2012; De Lara Resende et al., 2010). The results from these experimental studies primarily stem from lottery setups, very much in the same tradition as Ellsberg's original experiment (BOX 1). Some studies investigated risk and ambiguity preferences for more real-life events like betting on weather forecasts, stock indices or sports results (Abdellaoui et al., 2011; Fox and Weber, 2002; Heath and Tversky, 1991; Tversky and Fox, 1995). Much as with standard lottery setups, in these more real-life settings it remains a bet beyond the direct control of humans.

The main focus of this thesis is to examine the underlying decision processes regarding different types of uncertainty as well as social and non-social sources of uncertainty. I aim to understand if and why people differentiate between uncertainties that stem from a lottery, *state uncertainty* (or also referred to as *non-social uncertainty* in our individual Chapters), versus uncertainty that arises due to the actions of other people, *strategic uncertainty* (or also referred to as *social uncertainty* in our individual Chapters). Moreover, within these sources of uncertainty, I account for a broad spectrum of uncertainty by considering both risk and ambiguity.

To study why preferences for uncertainty might be processed differently between sources and types of uncertainty I employ a combination of both behavioral and neuroimaging methods. Moreover, to test whether DMUU and revealed preferences in the lab translate to real-life behavior I also examined participants' decisions outside the usual university laboratory. Such field research reduces experimenter control, but greatly helps in relating human preferences for risk and ambiguity in the lab to real-life DMUU. Theoretical models as well as implications for policies are based on experimental laboratory findings (Farber, 2011; Kocher et al., 2015), and therefore it is particularly important to confirm the external validity of experimental research related to both risk and ambiguity preferences. Ambiguity prefrences are given preferential treatment in this thesis, as precise probabilities relating to risk are seldom found in daily life (Post et al., 2008). Many studies link decision makers' risk preferences to decision-making outside the laboratory (Dohmen et al., 2011; Vieider et al., 2014; Rieger et al., 2014), but this does not fully address the notion of types of uncertainty.

Due to its rigorous theoretical underpinnings, DMUU often comes across as abstract and unrealistic. However, there are many examples where DMUU and the research topics in this thesis can be seen in daily life: In the medical domain models of DMUU are helpful in evaluating treatments and precriptions on the basis of survival rates, potential side-effects and the patients' individual willingness to take risks and accept ambiguity (Berger et al., 2013; Wakker, 2010). Other applications of DMUU can be found in buying insurance, financial investments or climate change (Millner et al., 2013).

Before I relate the research questions of this thesis with previous literature and discuss the research approach, I provide a historical context on these standard economic models of DMUU and how these have evolved.

1.2 Historical setting

DMUU is a cornerstone in microeconomic research. Historically, there have been numerous theories proposed to best describe DMUU. In general, one could say that earlier theories from the previous century envisioned DMUU as a normative tool to prescribe how human beings should behave (Wakker, 2010). Within this framework expected utility (EU) is the benchmark model in DMUU with objective probabilities (risk). This model is accompanied by a complete set of rules of behavior, formally known as axioms (von Neumann and Morgenstern, 1944). The gold standard in EU is rationality, which means that individuals should choose the option that obtains the highest utility. Savage (1954) extended EU to SEU for ambiguous events when no objective probabilities are available. He made use of the EU framework for risk (von Neumann and Morgenstern, 1944) and insights from de Finetti (1931) and Ramsey (1931) on subjective probabilities. See BOX 2 for a short explanation of EU and SEU and its most important axioms, the *independence condition* for risk, and the *sure-thing principle* for ambiguity, which were later adapted in new classes of DMUU models.

Based on the assumptions of SEU, a decision-maker is to be probabilistically sophisticated (Machina and Schmeidler, 1992). This means that she should be indifferent between a risky and ambiguous event if objective probabilities in the risky setting match beliefs in the ambiguous setting. For instance, let us assume that you believe that your favorite football team has an 80 percent chance of winning their next match. If they indeed win, you receive a monetary reward of €10, otherwise you will get nothing. The alternative option is to bet on the roll of a 5-sided die. You will win €10 if you roll the numbers one to four, and nothing if you roll five. Would you rather bet on your favorite football team to win the match, or the roll of a die? Your individual belief of 80 percent that your favorite football team will win the draw is matched with a corresponding objective probability of 0.8 in a die task. Based on SEU we were to conclude that a decision-maker should be indifferent between both choice options.

Empirically, this is not what we observe when human subjects complete this thought epxeriment. Most people shy away from uncertainty. They prefer risk to ambiguity, even more so when the underlying objective probabilities are higher than 0.5 (Abdellaoui et al., 2011). This behavioral phenomenon is known as *ambiguity aversion.*

Already in 1921, both Knight (1921) and Keynes (1921) proposed a clear distinction between these two types of uncertainty. Ellsberg empirically translated their insight into an influential experiment in 1961. The setup of his experiment is still widely used today to elicit individuals' ambiguity preferences. I will refer to it as the Ellsberg setup (see BOX 1). In the following chapters of this thesis, the Ellsberg setup is used to elicit ambiguity preferences.

After Ellsberg showed that probabilistic sophistication does not necessarily hold, more general models that could explain ambiguity aversion were developed (Abdellaoui et al., 2011; Etner et al., 2012). Savage's sure-thing principle (BOX 2) was regarded as the most stringent axiom, which was weakened by a first set of new ambiguity models which allowed for non-linear probabilities. One of the first alternatives to SEU was Choquet expected utility (Schmeidler, 1989). This model still assumes that people are able to form beliefs, yet Savage's sure thing principle (BOX 2) was relaxed. This idea of non-linear probabilities was further generalized in prospect theory by also adding a reference point, and as such an asymmetry of individuals' valuation of gains and losses (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Wakker, 2010). Newer classes of ambiguity models assumed that people are not able to assess precise subjective probabilities and proposed the use of multiple priors (different sets of probability distributions). Such models are called maxmin expected utility (Gilboa and Schmeidler, 1989) and a-maxmin expected utility (Ghirardato et al., 2004). Another popular ambiguity model is the smooth ambiguity model by Klibanoff et al. (2005) that rests on the idea that people formulate second-order beliefs (a prior over all priors), yet are not able to reduce these to compound lotteries. Finally, a more recent development, in line with our idea of sources of uncertainty, is the notion of source dependence (Chew and Sagi, 2006; Wakker, 2010). In line with Savage's terminology of 'small worlds', the idea here is to find domains for which decision-makers have well-established probabilistic beliefs. Within these small worlds it is assumed that people are ambiguity neutral. However, across domains, ambiguity aversion can arise.

BOX 1 The Ellsberg setup

Ellsberg created risky and ambiguous gambles with the attributes urns, balls and colors. Ellsberg implemented two different versions, namely the two-color and three-color Ellsberg problem. Below I describe the *two-color Ellsberg problem*, as researchers mostly use this version.

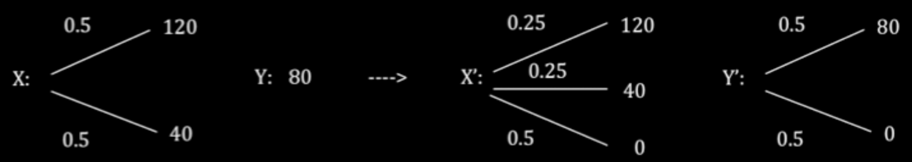
Please review the following setup: one urn contains exactly 5 black and 5 red balls and a second urn contains 10 balls in an unknown composition of either black or red balls. The first urn represents the risky urn as there is an equal objective probability of 0.5 to draw a black or red ball. The second urn is ambiguous as you do not know how many red or black balls are present. Mathematically, if one were to describe all the different combinations the ambiguous urn could have, taking into account the ten balls, the two available colors and the equal likelihood with which each combination could materialize, an underlying likelihood of 0.5 to either draw a black or red ball is expected. Nevertheless, a decision-maker is uncertain about the exact probability, and could potentially face a skewed urn with more red, respectively black balls. Based on this setup, the decision-maker is confronted with four different reward schemes (see below).

Choice options	$Black_r$	Red_r	$Black_a$	Red_a
1.0	€10	€0		
2.0			€10	€0
1.1	€0	€10		
2.1			€0	€10

$Black_r$ and $Black_a$ stand for a black ball drawn from the risky, respectively ambiguous urn, and vice versa for the red ball. First, a participant in this experiment has to choose between options 1.0 and 2.0: does she prefer to draw a ball from the risky urn when a black ball will result in a €10 gain, or else win nothing. Or does she prefer to draw a ball from the ambiguous urn in which a black ball will result in a similar gain of €10, else win nothing. After indicating this preference, she has to choose between options 1.1 and 2.1. Now drawing a red ball from either the risky or ambiguous urn will result in a gain of €10, else nothing. Majority of participants choose options 1.0 and 1.1. Let me explain why SEU does not hold here. A participant that prefers to bet on a black ball in 1.0 assigns a belief B to draw a black ball from the ambiguous urn that is less than the objective probability of 0.5 to draw a black ball from the risky urn: $B(Black_a)<0.5$. One might conclude from this observation that majority of participants believe the ambiguous urn to have more red than black balls and thus expect $B(Red_a)>0.5$. However, majority of participants also prefer to bet on a red ball in the risky urn in choice option 1.1, indicating that: $B(Red_a)<0.5$. Both preferences lead to non-additive beliefs, as both: $B(Black_a)+B(Red_a)<1$. This finding contradicts SEU and is coined ambiguity aversion. Ellsberg concluded that people prefer risk to ambiguity, because they dislike uncertainty and therefore mostly choose to bet on drawing balls from the risky urn.

BOX 2 Expected utility and subjective expected utility

Risk entails events, which outcomes materialize with known probabilities. For instance, imagine that you could win €5 if a coin tosses head and €0 when it tosses tail, each with 50 percent probability (p=0.5). How much is this bet worth to you? The expected value is: 0.5*5 + 0.5*0 = €2.50. Now consider the same setup, but with the following outcomes. You could win €1000 if head faces up, and €0 in case of tail. The expected value of this gamble is €500. If I would offer you a choice between playing this last coin gamble and receiving €500 for sure, you would most probably go for the sure option. The larger the money at stake the less risk you are willing to take by playing the gamble. It was Bernoulli (1738) who, based on this logic, introduced the idea of EU. Depending on your risk preferences, a utility function is attached to outcomes before it is multiplied by corresponding probabilities. Von Neumann and Morgenstern (1947) subsequently defined axioms, which can be understood, as a set of choice preferences people ought to apply. Please consider one of the most important axioms, *the independence condition*, which von Neumann and Morgenstern (1947) derived based on EU. This axiom postulates that a preference for one lottery over the other should remain intact when the lotteries get mixed with another lottery. For instance, lottery X leads to an outcome of 120 or 40 with equal probability, whereas lottery Y leads to a sure outcome of 80. If I would add a lottery with zero mean and the original lotteries X and Y multiplied by 0.5 (see decision tree below as illustration), people should not switch preferences. That is, if they preferred X to Y, they should still prefer X' to Y', and vice versa.



Maurice Allais showed that many people do not satisfy a preference relation in line with the independence condition (1953). When probabilities are not known, and we thus speak of ambiguity, SEU postulates that people use their inference to construct their own expectations, formally known as subjective probabilities. The foundation of EU is merged with the idea that people construct subjective probabilities (Savage, 1954). The most important axiom in SEU is the sure-thing principle. It means that the preference for a certain lottery X over Y is not influenced by common outcomes. For instance, if event E1 can lead to outcome α or X and event E2 leads to outcomes α or Y, then the preference between E1 and E2 should be solely determined by the outcomes X and Y. Now consider events E3 and E4, which respectively lead to outcomes β or X and β or Y. If a decision-maker prefers to bet on event E1, she should also prefer to bet on event E3 as the common outcome Y should be disregarded.

The goal is to define such small worlds and based on de Finetti's idea of exchangeability a model is formulated (Etner et al., 2012).

Besides formulating these new theoretical models of DMUU, experimental research began to identify moderators of ambiguity aversion after Ellsberg's findings. For instance, ambiguity preferences are influenced when elicited in isolation and not directly in comparison with risk (Fox and Weber, 2002; Qiu and Weitzel, 2011). Ambiguity aversion, but not risk aversion, is also reduced when participants need to reveal to reveal their choices amongst their peers (Curley et al., 1986; Trautmann et al., 2008). However, jointly deciding in group settings leads to more ambiguity neutral choices (Keller et al., 2007; Charness et al., 2013).

Overall, we can conclude that a new area of research began to arise in reaction to Ellsberg's finding, and simultaneously as a reaction to Maurice Allais (1953), who empirically challenged EU as a descriptive model for risk by showing that people do not behave according to the independence condition (BOX 2). Ellsberg and Allais empirically showed that the axioms of a model could be tested and therefore directly refuted or validated. At this time, von Neumann and Morgenstern (1944) and Savage (1954) acknowledged that their goal was to prescribe how an individual should behave, and thereby realized that in reality they might not do so. Ellsberg and Allais wanted to model and describe how people actually behave (Heukelom, 2015) albeit at the cost of parsimonious theory. This has led to an era in which "economics became a behavioral science" (Heukelom, 2015, p. 167), and "economics has been opening up to introspective and neuroimaging data" (Wakker, 2010, p. 3).

The research approach in this thesis stems from the above mentioned developments in the economic literature as I use several methodologies in order to understand the mechanisms with which people make certain decisions. This includes the use of neuroimaging data, which is a relatively new endeavor in economics and is also known as 'neuroeconomics'.

1.3 Neuroeconomics

The interdisciplinary field of neuroeconomics combines insights from economics, psychology and neuroscience (Sanfey et al., 2007). All three disciplines share the same goal within decision sciences: to understand the choices of human beings.[2] Neuroeconomics aims to contribute to decision sciences by accumulating knowledge from these three disciplines (Glimcher and Rustichini, 2004). The contribution of neuroscience to economics is that it maps a neural circuitry that describes and explains behavioral output (Sanfey et al., 2006; Loewenstein et al., 2008). Technological advances in neuroscience have allowed neuroeconomic researchers to analyze the neural mechanisms that underlie behavior (Camerer, 2013). There are many methodologies to measure neural activity, but functional magnetic resonance imaging (fMRI) is the most commonly used in neuroeconomic research, due to its high spatial resolution. BOX 3 describes the basic concepts of this technique.

Decision-making is a highly developed cognitive ability, requiring an interplay of elementary processes like attention, visual perception, motivation and cognitive control. Behaviorally, it is difficult to tease apart these underlying decision processes, but fMRI methods offer us a tool to empirically investigate the underlying neural mechanisms a decision-maker uses to reach a decision.

One of the first fMRI studies of DMUU came from Platt and Glimcher (1999). Their research with monkeys demonstrated that neurons in the lateral parietal cortex, a region known as LIP, are active when animals act on priors as well as posterior probabilities. Subsequently, this finding was also replicated in humans when decisions are made under uncertainty (Huettel et al., 2006; Bach et al.,

[2] The influence of psychology in economics is not new and has led to the rise of behavioral economics (Rabin, 2002). Insights from psychology have outlined a collection of heuristics and biases people use as rules of thumb to guide their DMUU (Tversky and Kahneman, 1981). Prospect theory is a direct result of the translation from descriptive choice behavior to standard economic models (Kahnemen and Tversky, 1979; Tversky and Kahneman, 1992). This model is seen as “the first descriptive theory that explicitly incorporated irrational behavior in an empirically realistic manner while at the same time being systematic and tractable” (Wakker, 2010, p. 2).

2009). These studies demonstrate that neurons in the LIP region carry information about prior probabilities, which is used by both monkey and human decision-makers to select the most rewarding option.

I find it important to note that Platt and Glimcher's experiment (1999) was greatly influenced by a debate on the exact role of the LIP. Namely, previous research (Anderson et al., 1987; Colby et al., 1996) was inconclusive as to whether signals in the LIP carry sensory or motor input, and either attention or intention. Platt and Glimcher (1999) offered a new perspective on the role of the LIP (Glimcher, 2004) by taking an economic approach to a visual experiment, the cued saccade experiment. This research also provided a first outline of a neural mechanism for DMUU. For me, this illustrates two important points. First, that understanding basic neural elementary processes, like vision and attention, can influence economic hypotheses pertaining to decision-making, and second, that an economic perspective also adds value to neuroscience by relating concepts like probability and value to elementary realms of experimentation like vision and attention. In the same way psychological insights were fruitfully combined with economic models of utility, neuroscientific contributions may stimulate new economic models of decision-making (Glimcher and Rustichini, 2004).

Neuroscientific research has focused on two issues relavant to this thesis, namely the importance of probabilities and value on decision making, and the comparison between social and non-social interactions (i.e. sources of uncertainty). There is little research however - with the exception of some notable publications (Corricelli and Nagel, 2009; Hampton, et al., 2008)[3] - investigating the combination of these two features of strategic uncertainty.

Ambiguity aversion is known to have a distinct neural basis, and the few fMRI studies on ambiguity hint at two potential mechanisms. One proposed mechanism focuses more on emotional processes (Hsu et al., 2005), whereas the other promotes more abstract computational mechanisms (Huettel et al., 2006; Bach et al., 2011). It is problematic to reach conclusions in order to pinpoint the exact underlying

[3] These fMRI studies focus on mentalizing abilities of humans, but do not consider their studies within the framework of DMUU.

mechanisms leading to ambiguity aversion as the research designs of these fMRI studies differ to quite some extent, it

The literature on neural differences when people interact with humans instead of lotteries does not distinguish between risk and ambiguity (McCabe et al., 2001; Delgado et al., 2005; Kosfeld et al., 2005; Amodio et al., 2006; Saxe et al., 2006; Behrens et al., 2008; 2009). The fMRI study that comes closest to investigating strategic uncertainty within the domain of DMUU is by Aimone et al. (2014). They study the neural mechanisms of strategic ambiguity, yet do not consider risk. Their fMRI results stress the relevance of the right anterior and posterior insular cortex when subjects decide to trust others in comparison to a computer-mediated treatment. The insula is a region in the midbrain that is engaged with a wide variety of negative emotions like disgust (Sanfey et al., 2003). Therefore, Aimone et al. (2014) interpreted activation in the insular cortex to reflect the heightened negative state of betrayal aversion.

In this thesis I offer a new perspective on the neural basis of ambiguity preferences by allowing for individual variation in ambiguity preferences, which arises due to humans' attitudes towards (the interaction of) types and sources of uncertainty. These neuroimaging results offer insights into the underlying decision-processes of DMUU.

1.4 Contributions and overview

Extending uncertainty beyond lotteries

When Von Neumann and Morgenstern introduced EU in 1944 they intended to analyze individual risk taking in strategic game situations. They assumed strategic uncertainty where a decision-maker incorporates the expected utility and best response of other players in order to maximize her own utility. In their framework, the probability of receiving a good outcome is independent of the source of uncertainty. In other words, a decision-maker should equally evaluate a 50 percent chance to win a gamble when it stems from a random mechanistic device or from somebody else's conscious decision.

BOX 3 fMRI experiments

fMRI stands for functional magnetic resonance imaging. This technique makes use of MRI (magnetic resonance imaging) technology to be able to localize brain activation. Brain activity, which means certain brain cells (neurons) are actively engaged to perform a certain task, is accompanied by an increase in blood oxygenation. Quite literally, these active brain regions require oxygen, which serves as fuel for this region. Via fMRI we measure changes in blood oxygenation: the difference in magnetization between oxygenized and deoxygenized hemoglobin. The signal the MRI scanner records with fMRI is what we label as BOLD (Blood Oxygenation Level Dependent) and this signal serves as our dependent variable when analyzing neuroimaging data. In contrast, standard MRI is not tuned to changes in blood oxygenation, but outlines anatomical structures of the brain (or any part of the body) without any connection to actions or decisions, which are evoked by experiments when applying fMRI.

fMRI is a non-invasive technique, in contrast to, for instance, single-cell recording. When placing an electrode near or within a neuron one is able to record the actual activation of that neuron. With healthy human subjects it is ethically impossible to place an electrode within the brain, and thus fMRI is as close as we can get to precisely indicate where in the brain activation takes place. Although electroencephalography (EEG) is able to directly measure the electrical and magnetic activity from within the brain by placing electrodes on the human skull, this measure has a bad spatial resolution. It cannot precisely indicate *where* in the brain the activation stems from. fMRI offers us a technique to localize brain activity within millimeters of its origin. EEG is, however, more precisely in indicating *when* the activation occurred (high temporal resolution). In contrary to its high spatial resolution, fMRI offers low temporal resolution, as the BOLD response is a correlational measure of the actual neural activity (Huettel et al., 2009).

How can we infer meaning to our findings once we have done proper preprocessing on our raw BOLD signal and are able to indicate where in the brain activation occurred during certain decision-making tasks? Knowledge about specific processes of brain areas comes from lesion studies and animal research (Huettel et al., 2009). If patients with brain damage to certain brain areas are unable to perform a specific task compared to healthy controls, this reveals a causal relationship between the brain and some action. With animals, permanent lesions can be investigated and this increases our knowledge about brain regions and their necessity for specific functions. In humans, a common approach to link brain activity to a particular cognitive process is ‘reverse inference’. However, we need to be careful with this approach, as the BOLD measurement is, in essence, correlational. With the help of neuroimaging databases, we can formally describe which cognitive process is most likely as a result of brain activity within a particular experimental design (Poldrack, 2006).

This is often not the case, as experimental studies have found that decision-makers behave differently towards sources of risk and ambiguity (Abdellaoui et al., 2011; L'Haridon et al., 2013). Amos Tversky was the first to speak about sources of uncertainty, which he defined as groups of events that are generated by the same mechanism of uncertainty, and thus have similar characteristics (Abdellaoui et al., 2011). Sources of uncertainty could also explain why people are equally willing to exchange a bet on a specific color of the ball in the risky and ambiguous urn in the Ellsberg setup (BOX 1), but dislike exchanging their bet on a particular colored ball between the urns. The willingness to exchange within but not between urns implies that the same urn is one specific source of uncertainty, but the risky and ambiguous urns are considered two different sources of uncertainty (Wakker, 2010).

Social sources of uncertainty have not been studied often (Trautmann and Vieider, 2011). However, in real-life uncertainy rarely stems from some sort of random device, like a color of a drawn ball from an urn, the flip of a coin, or the roll of a die. As Trautmann and van de Kuilen (2013, p. 600) explain in their review of ambiguity, "real life is not about balls and urns". Human beings are social beings, and thus some of the uncertainties we face are due to the actions of other human beings. Even very subtle social influences can have an impact on human's decision-making (Asch, 1956; Reno et al., 1993).

Nonetheless, in the historical tradition of EU and SEU, risk and ambiguity are still primarily elicited via lottery setups. The most common elicitation methods for risk include choosing to allocate resources between a safe and risky asset (Gneezy and Potters, 1997), a single choice between a set of different gambles (Eckel and Grossman, 2002) and a multiple price list procedure, which the risky lottery setup by Holt and Laury (2002) is frequently used (Charness et al., 2013). Ambiguity, on the other hand, is primarily measured via the Ellsberg setup (BOX 1), which can essentially be considered a lottery setup.

Since the last decade there has been a shift and experimental economics has outlined the effects of social preferences, fairness considerations, and intentions of other decision-makers (Andreoni and Miller, 2002; Fehr and Schmidt, 1999; Falk and Fischbacher, 2006). A common experimental approach to compare social and non-social sources of risk is a trust decision, typically administered experimentally with the Trust Game from Berg et al. (1995).[4] A trust decision involves strategic uncertainty, as the Trustor must form a belief about the risk of betrayal by the Trustee and, given this subjective probability of betrayal, either decides to trust or not (Coleman, 1990). Interestingly, although placing trust in someone is intuitively risky, experimental evidence on risk preferences, stemming from a lottery, and trusting behavior is mixed. Houser et al. (2004) find no correlation between trust and lottery risk, whereas Schechter (2007) does find a positive correlation. Also, some studies find that aversion to risk is strongest in the Trust Game versus a comparable lottery context (Bohnet and Zeckhauser, 2004; Aimone and Houser, 2008). This finding was labeled betrayal aversion (Bohnet and Zeckhauser, 2004). It implies that participants show more risk averse behavior in a strategic uncertainty context, as compared to a lottery context, because they dislike being betrayed by a person who consciously decided not to reciprocate an investment.

In the next Chapter of this thesis, titled Trust and Risk revisted, I[5] reflect on these mixed experimental results regarding trust and risk. As there is no clear evidence for a link between lottery risk preferences and risk involved in trusting others I argue that sources of risk should be considered as a possible explanation. Namely I propose that there is a crucial difference between risk measurements in the two settings. Trusting involves giving up control to another human while lottery risk arises from a mechanistic randomization device. In this Chapter I designed a risky Trust Game that experimentally measures risk in the same context as the standard Trust Game, but reduces the trust decision to objective risk. The results show that transfers in the Trust Game can indeed be explained by individual risk attitudes elicited with

[4] In this game there are two players, which are known as the Trustor and Trustee. The Trustor is usually endowed with 10 tokens and can choose to invest some of her tokens with a Trustee. The experimenter usually triples this investment before it reaches the Trustee. The Trustee can return some of this tripled investment to the Trustor, but is free to keep the whole investment to him- or herself. The Trustor needs to offset the possibility of receiving back a multiplier of her investment versus the risk of losing a great part or even the complete investment. Trust is quantified as the amount a Trustor invests with a Trustee.

[5] Although I write the Introduction from my own perspective, the individual Chapters are without no doubt a collective product of me and my (co)-superisors.

the risky Trust Game, while lottery risk preferences have no explanatory power.

In this thesis I also put forward the idea that types of uncertainty should be considered, as many uncertainties in real-life cannot be captured by objective probabilities. Also when it comes to social sources of uncertainty, we rarely know the exact probability of other decision-makers' moves. In a Trust Game setting, you could speculate that you only know, with quite some certainty, the rate of reciprocation if the Trustee would be your best friend. Generally, we cannot assess such precisce probabilities in our day-to-day social interactions with others. Yet, experimental studies primarily focus on comparing social versus non-social sources of risk as specific type of uncertainty. Only Aimone et al. (2014) studied betrayal aversion in the context of ambiguity.[6]

In Chapters 3 and 4 I investigate both types and sources of uncertainty simultaneously in a single MRI experiment. In the social context I adapted the standard Trust Game (Berg et al., 1995), as described above, to evoke social uncertainty. For the non-social context I used the typical Ellsberg lottery setup. In both settings, participants could choose between six discrete investment amounts: 0, 2, 4, 6, 8 or 10 tokens. This investment was tripled and was either placed in the lottery, or was sent to another, real person who had previously made a return choice in the role of Trustee in the Trust Game. Additionally, there were two different types of uncertainty regarding the likelihood of their investment being repaid. Ultimately a total of four experimental conditions: a risky Trust Game, a risky lottery, an ambiguous Trust Game and an ambiguous lottery were impletemented. This implicated that participants faced choices in which they explicitly knew the probabilities of either a reciprocating Trustee or a ball with a winning color respectively (risk conditions), or where these probabilities were unknown (ambiguity conditions). It was challenging to simultaneously

[6] Notable exceptions are studies, which address ambiguity preferences to strategic games by comparing behavior in dyadic risk and ambiguous games (Pulford and Colman, 2007; Eichberger et al., 2009). These contributions aim to show that ambiguity aversion plays a role in interactive decision-making and should be considered as an important preference in its own right in game theory.

study DMUU in a social and non-social context, as underlying subjective probabilities can be easily manipulated in a lottery context[7], but people have more idiosyncratic expectations in social environments. It is essential to address these individual beliefs in order to have a useful comparison between our different treatments. This design took this into account by matching individual beliefs - regarding the ambiguous social interaction - to the other decision contexts, in order to ensure that any observed differences could be attributed to either the type or source of uncertainty respectively. Namely, I elicited participants' beliefs, stemming from the Trust Game, by asking participants how many Trustees they thought would likely reciprocate their investment. This prediction was then used to align individual beliefs in the social context with a similar underlying likelihood of drawing a winning colored marble in the ambiguous lottery. Subsequently, participants received objective probabilities in a risky lottery and risky Trust Game that matched their individual social prediction. Taking these individual beliefs into account also allowed me to explore individual differences in ambiguity preferences.

In Chapter 3 I examined the decision-making phase of the experimental design discussed above. I found a significant behavioral main effect of ambiguity aversion. Participants invested less when the type of uncertainty was ambiguous as compared to when it was risky. When I took sources of uncertainty into account, this aversion was only observed in the social domain. Secondly, I found that ambiguity preferences were dependent on individual beliefs. That is, when individual beliefs were taken into account, ambiguity aversion was only part of the overall picture. In the social context, ambiguity aversion increased as individuals held higher expectations concerning the reciprocity of Trustees. In the non-social context I did not observe such a linear relationship between beliefs and ambiguity preferences. These individual differences were also reflected in the neuroimaging results where significant clusters of brain activity related to individual social ambiguity preferences but not to lottery ambiguity preferences.

[7] For instance, by changing the two-color urn in an Ellsberg setup (BOX 1) to a ten-color urn in which either 1 color is a winning color, or nine colors are winning color, the underlying likelihood changes from 0.5 in a two-color urn to 0.1 respectively 0.9 in a ten-color urn.

Specifically, the inferior frontal gyrus (IFG) consistently correlated with individual social ambiguity preferences. These findings are supported by results indicating that the IFG is involved with social cognition (Oberman et al., 2007).

In Chapter 4 I specifically looked at the outcome phase of the experimental design discussed above. Here fMRI participants anticapted their outcomes as they were confronted with their previous decision-making. From an economic perspective this might seem like an odd approach, as there was no actual decision-making taking place anymore. However, reward anticipation is a well-studied topic in the field of Neuroeconomics. I aimed to contribute to this literature by incorporating the design I had established, which allowed me to investigate expected reward signals by examining the effect of both sources and types of uncertainty, while taking participants' beliefs into account as well. This approach differs from the standard neurscientific approach, which is based on conditioning experiments in which arbitrary cues signal positive and negative rewards. Here, I investigated whether decision-makers' beliefs about the outcomes of their choices can also act as a cue for reward anticipation, or in other words, when the reward cue is a function of prior internal evaluations as opposed to an externally-provided association. My neuroimaging analyses focused on whether belief-related expectation signals were evident in brain regions related to standard cue-based reward anticipation. I found confirmatory evidence of this, with the greater the expectation of receiving a back-transfer in the Trust Game, the greater the investment amount, and in turn the higher the activation in a region encompassing the left ventral caudate and nucleus accumbens. This novel result illustrated that one's own investment choice, modulated by expectations regarding receivers' reciprocating behavior, served as a similar type of anticipatory cue from standard conditioning experiments. Interestingly, I did not find a similar anticipated reward signal in the lottery contexts. In Chapter 4 I further speculate about these findings based on the neuroimaging results.

Extending the scope of uncertainty beyond the laboratory

Many theoretical contributions use experimental evidence on ambiguity to include it in models when aiming to simulate real-life phenomena like the equity premium puzzle, the stock market participation puzzle, and the home bias (Guidolin and Rinaldi, 2013). Policy makers use experimental insights on ambiguity to propose and construct new policy measures (Farber, 2011). Predicting how people will behave to certain economic stimuli is important for designing policy institutions (Farber, 2011). This raises questions regarding the external validity of DMUU elicited in the laboratory. We assume that we can generalize our findings from the laboratory to human beings' behavior in the real world (Levitt and List, 2007), but do our measures from the laboratory actually capture meaningful predictors of DMUU?

It is important, both scientifically as well as practically, that laboratory measures of uncertainty capture a meaningful feature of peoples' preferences for uncertainty in the real world. Only then can experimental insights be fruitful and serve as an indicator of how people might respond when introducing new policy measures or when changing the decision landscape.

While in economics it is generally assumed that preferences for risk and ambiguity are context independent, in psychology, it is common to assume that the context and the situation play an important role (Weber and Johnson, 2008). The latter argues against the universal external validity of context-independent preferences and for eliciting risk preferences per different decision domain (Weber et al., 2002).

In order to resolve this controversy, a few experimental studies have elicited preferences for uncertainty, and have done so by taking the underlying decision context into account. Subsequently they relate these measures to real-life behavior in order to assess if one general overarching preference for uncertainty can be used, or domain specificity is more prominent. The results of these studies are mixed. Although several risk measures from different domains, including survey questions and lottery measures, are correlated (Einav et al., 2012; Dohmen et al., 2011; Lauriola et al., 2007; Vieider et al., 2014), their predictive power does not always translate from the laboratory to the field.

Dohmen et al. (2011) used survey questions to elicit risk, which positively correlate with risk elicited via a lottery setup, and show that the most general risk question is the best overall predictor for real world risky behavior. On the other hand, they also stress that the best predictor in a specific real-life risky context is best represented by an elicitation procedure that incorporates the corresponding context. For example, the best independent variable of smoking behavior is the survey question that measures risk in the health domain. Dohmen et al. (2011) stress that survey measures of risk can be used as a reliable measure that is cheap and fast in order to collect data on risk preferences in big samples, but some studies claim the opposite. For instance, Pennings and Smidts (2000) show that real world risk averse strategies by Dutch hog farmers cannot be predicted by survey measures on risk, and is better predicted by standard risky lottery measures.

Also in the field of developmental economics, studies have tried to relate risk preferences to basic features of human preferences in the developing world. Tanaka et al. (2010) showed that mean village income is significantly positively correlated with risk aversion. Liu and Huang (2013) showed that more risk averse cotton farmers in China use greater quantities of pesticides. Cole et al. (2013), however, found, in contrary to their hypothesis, that more risk averse Indian farmers are less likely to take up insurance.

A critical reader might wonder why most of the empirical work discussed so far is only based on risk preferences. Still most empirical studies do not take preferences for true uncertainty, or ambiguity, into account. Despite numerous experimental studies on ambiguity preferences in the laboratory, there are relatively few empirical studies on ambiguity preferences in the field and/or with participants other than university students. The few empirical studies on the external validity of ambiguity aversion show a positive relationship with smoking behavior in adolescents (Sutter et al., 2013), and negative relationships with retirement planning (Dimmock et al., 2015a), adoption of new varieties of crop (Engle-Warnick et al., 2007) and new variety of rice (Ross, 2012). Nonetheless, Trautmann and van de Kuilen (2013) claim in their review on ambiguity that ‘there is too little convincing evidence so far on the external validity of ambiguity attitudes' (p. 597).

In Chapters 5 and 6 I aimed to close this gap by conducting two experimental studies in which I related both risk and ambiguity preferences to real-life decision-making. Also, in Chapter 6 our population pool consisted of adolescents instead of university students, which are normally used as participants in experimental studies.

In Chapter 5 I studied the external validity of ambiguity attitudes[8] on real-life decision-making in the context of student loans in The Netherlands. Although a substantial proportion of students (35%) in the Netherlands take out student loans (Nibud, 2012), the majority prefers to finance their studies with a part-time job. This negatively affects the total study duration. Student borrowing is therefore an important policy instrument for the Dutch government. Students' risk preferences have been related to the take up of student loans (Oosterbeek and van den Broek, 2009), but ambiguity preferences have not been considered so far. We argue that taking out student loans is less about risk, but more about ambiguity. Students' aversion to borrowing may be primarily driven by their aversion to ambiguity regarding the repayment of their loans. Specifically, students are uncertain if they will be able to repay their debt after having obtained a degree, and also if they will graduate in the first place. Secondly, Dutch students face a multitude of ambiguous elements in the decision to take out a loan, including uncertain interest rates. Accordingly, we expect that students who are more ambiguity averse will borrow less than other students. We elicited ambiguity attitudes experimentally and not with survey questionnaires, which is the most commonly used approach to understand students' borrowing behavior. Ambiguity attitudes were measured based on matching probabilities of three uncertain events with the following likelihoods: 0.1, 0.5 and 0.9 (Abdellaoui et al., 2011; Dimmock et al., 2015a; 2015b). After eliciting participants' ambiguity attitudes, students answered a variety of questions concerning their borrowing behavior. I found a negative relationship between a student's ambiguity aversion and the amount

[8] Ambiguity attitudes encompass both ambiguity preferences and insensitivity. In Chapter 5 I discuss insensitivity in greater depth.

she borrows, and no relationship between risk and borrowing behavior. These results have important policy implications, which I further address in Chapter 5.

In Chapter 6 I conducted an experimental study on DMUU with adolescents. Sutter et al. (2013) has primarily looked into the relationship between risk and ambiguity and health-related variables such as smoking and drinking. In this Chapter I related adolescents' preferences for risk and ambiguity to their mental health. Specifically, I tested if risk and ambiguity preferences correlated with their degree of self-confidence, which is a concept composed of self-belief regarding own capabilities and social standing. Social standing is an essential defining feature of adolescence, as adolescents have a strong desire for social relatedness and are very sensitive to processing information concerning social evaluation and social standing (Somerville, 2013). At the same time, adolescents' social relationships are rather instable as friends come and go, and adolescents will experience peer rejection more often compared to other age groups (Wang et al., 2009). Therefore, I hypothesized that those adolescents who are more risk and ambiguity averse are at the same time less confident regarding their social standing. I tested 187 children at one high school, with an age range of 12-17 years. Risk and ambiguity were measured via a standard Ellsberg setup. In a choice list format adolescents had to choose between drawing a ping-pong ball from either a risky or ambiguous urn, or alternatively receiving a sure amount. As the sure amount increased, participants tended to switch from drawing from the urn to choosing the sure amount. From each individuals' switching point, a certainty equivalent was inferred and served as an indication of individual risk and ambiguity preferences (Wakker, 2010). The school provided a range of demographic data, school grades, independent intelligence scores and psychological measures on well-being, self-confidence, and motivation. On average, I found that adolescents are risk neutral, but at the same time ambiguity averse. Surprisingly, risk and ambiguity preferences were negatively correlated. Girls expected substantially more winning colored ping-pong balls in the ambiguous urn, though this did not result in greater ambiguity seeking behavior. When relating adolescents' preferences for risk and ambiguity to levels of self-confidence, I found that their risk aversion correlated with self-confidence. In particular, risk aversion affected the way adolescents' rated their own social skills at school. We did not find a relationship between ambiguity and self-confidence. In Chapter 6 I further reflect on these findings.

Altogether, this thesis investigates how sources and types of uncertainty affect individuals' decision-making and their external validity. In the next Chapter I will focus on social and non-social sources of risk before I include ambiguity as a type of uncertainty in our fMRI experiments in Chapters 3 and 4. Finally, Chapters 5 and 6 will address the external validity of sources and types of uncertainty.

Chapter 2

Trust and risk revisited[9]

Introduction

A crucial element of trust is "the willingness to increase one's vulnerability to another person whose behavior is not under one's control" (Zand, 1972). Namely, a Trustor is always confronted with the possibility that her trust might not be honored. A trust decision, therefore, involves strategic uncertainty: a Trustor forms a belief about the risk of betrayal by the Trustee and, given this subjective probability, decides to trust or not. Moreover, if a Trustor is confident about the probability of betrayal, say 50 per cent, she actually faces a lottery with corresponding outcomes and 50 per cent chance of losing. One could therefore argue that a Trustor faces a risky choice in the Trust Game when she acts upon her belief regarding the chances of betrayal by the Trustee (Coleman, 1990).

But do individual risk attitudes indeed explain trust? Many experimental studies have attempted to answer the question above, but could not identify a clear link between trust and Trustors' risk preferences (Eckel and Wilson, 2004; Ashraf et al., 2006; Ben-Ner and Halldorsson, 2010; Houser et al., 2010; and Etang et al., 2011).[10]

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[9] This chapter is based on a joint paper with Alan Sanfey, Jana Vyrastekova, and Utz Weitzel: 'Trust and Risk Revisited', 2014, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2524281.

[10] Subjects' risk preferences are measured by a variety of tools, e.g. by questionnaires like Zuckerman's sensation scale (Eckel and Wilson, 2004), a lottery setup with a menu of pair wise comparisons of two lotteries (Holt and Laury, 2002, Eckel and Wilson, 2004, Houser et al., 2010; Corcos et al., 2012), or by a task involving a choice between a lottery and a sure option, which mirror the distribution of outcomes in the Trust Games (Eckel and Wilson, 2004; Schechter, 2007; Ben-Ner and Halldorsson 2010), or not (Etang et al., 2011).

We argue that this is due to a mismatch between the measurement of risk and the type of risk a Trustor faces in the Trust Game. The lottery setup, which has been typically used to elicit individual risk attitudes, does not fully capture the risk a Trustor faces in the context of the Trust Game and thereby distorts the measurement of risk attitudes that are relevant in trusting behavior.

The essential difference between lottery risk and the risk taken in a Trust Game is that the former stems from a mechanistic randomization device while the latter stems from a conscious choice made by another human being. These different sources of risk can affect behavior even if both have the same objective probabilities and outcomes (Abdellaoui et al., 2011). Such different responses towards human and mechanistic sources of risk can have many reasons. Losing money to a randomization device (nature) can be perceived as bad luck, but incurring a loss to another decision-maker might be interpreted as wrong judgment; a signal of failure to assess the social situation properly (Trautmann et al., 2008); or as an exposure to conscious betrayal (referred to as 'betrayal aversion' by Bohnet and Zeckhauser (2004), and corroborated by Aimone and Houser (2012)). Intentionality may be another reason (Falk and Fischbacher, 2006). Imagine that John wants to drive home and has to choose between two roads. On both there is an equal objective risk of crashing because of a branch that may lie on the road. On one road the branch may have fallen off a tree by accident. On the other road a human may have intentionally broken off the branch. As the sources of risk differ, John may have a clear preference for the first road, although the probabilities and the direct outcomes are identical for both. Thus, a misalignment in the sources of risk might explain why previous studies could not find a link between risk that originates from a lottery and from a situation of trust.

The objective of this study is to identify the role of risk in trust and to suggest a novel measure of risk that is measured in the same context as the *'standard Trust Game'* (STG) by Berg et al. (1995). To elicit risk attitudes in the context of trusting, we developed a '*risky Trust Game*' (RTG) where risk, as in the STG, stems from a conscious decision of another person. We also measure lottery risk preferences by a standard lottery setup (Holt and Laury, 2002), which has been used by most studies that try to find a relationship between risk and trust (Eckel and Wilson, 2004; Houser et al., 2010; Corcos et al., 2012). We then relate both lottery risk preferences and risk preferences measured in the RTG to Trustors' invested amount in the Trust Game.

We hypothesize that individuals' risk preferences stemming from the RTG influence Trustors' decisions in the Trust Game, but lottery risk preferences do not. In both cases, the decision-maker faces pure risk, captured by objectively known probabilities of possible states of the world. However, in the lottery setup, the outcomes materialize due to the properties of the lottery mechanism, while the outcomes in the RTG were generated by a conscious choice of a human being.

In our RTG, the Trustor objectively knows the probability that a Trustee will honor her trust, and has to make a decision whether to trust or not. The fact that the probability of trustworthiness is objective and correct is guaranteed by implementing a conditional lottery design (Bardsley, 2000). We randomly match the Trustor to one out of four Trustees who decided individually and independently to honor trust or not. When deciding whether to trust and, if so, with which amount, the Trustor knows that either none, one, two, three or all four Trustee(s) are trustworthy. We ask the Trustor to decide for each of these five possible scenarios which amount she would transfer to a randomly matched Trustee. Hence, depending on the scenario, the Trustor knows that the probability to be matched with a trustworthy Trustee is either 0, 0.25, 0.5, 0.75 or 1.0. At the end of the experiment only one of the five scenarios, determined by the real return decisions made by Trustees, is payoff-relevant for the Trustor. Like a lottery, this RTG replicates a risky bet on a set of outcomes with objective probabilities. The essential difference is that the risk in the RTG stems from the decisions of other people and not solely from a mechanistic device. Hence, the decision in the RTG captures the effects of a Trustor's vulnerability to another person (Trustee), who is better off when keeping a Trustor's transferred investment for himself.

To analyze a possible link between risk and trust we investigate the relationship between subjects' risk preferences elicited in the RTG and Trustors' decisions in a STG, which builds on Berg et al. (1995). In the STG, we also randomly select one Trustee from four possible Trustees for reasons of implementation comparability. The only difference between the risky and the STG is that, in the latter, the Trustor cannot condition an investment level on an objectively known probability distribution of trustworthiness among Trustees.

Our experimental results show that risk preferences, measured in the RTG, strongly predict transfers in the STG, while lottery risk preferences (Holt and Laury, 2002) do not. These results are robust in bivariate and multivariate settings and also in regressions where both risk measurements are included together. Moreover, we find that risk preferences measured in the RTG setting and lottery risk preferences are not correlated with each other, supporting the notion that sources of risk matter (Abdellaoui et al., 2011; L'Haridon et al., 2013). Altogether, these results indicate that individual risk attitudes can predict trusting decisions, but only when elicited in the same context as the decision to trust.

This paper contributes to the continuing discourse on the role of risk in trust decisions, in particular to the following studies that attempted to analyze and elicit risk attitudes in trust-related settings.

Bohnet and Zeckhauser (2004) provide the first attempt of a direct assessment of risk in a trust setting. In their experiments with a binary Trust Game, they elicit the minimum acceptable probability (MAP) of being matched to a trustworthy Trustee for which the Trustor would choose to trust. This design ultimately converts the trusting decision into a decision under risk, because the Trustor can condition trusting on the (subjective belief of the) trustworthiness of the Trustees. The authors show that such a trusting decision is more than betting. Trustors reveal a higher willingness to bet on "trust" when a lottery generates the outcomes than when Trustees decide. The authors refer to the costs of losing control to the benefit of Trustee as *betrayal aversion*.

Although Bohnet and Zeckhauser (2004) find that decisions differ between trust and risk environments, this is not supported by Kosfeld et al. (2005) and contradicted by Fetchenhauer and Dunning (2012). Houser et al. (2010) argue that the conflicting results can be due to the fact that the analyses are based on aggregate data analyses of distributions between games. By collecting individual-level data on risk attitudes, Houser et al. (2010) control for individual heterogeneity. Their experimental design consists of four variations of the Trust Game.

In two of them, the decision-maker places a bet, and the return is decided by a computer according to a known probability distribution. The return decision either affects only the decision-maker, or it also affects a dummy player. Comparison of these two variants allows addressing the role of social preferences in placing the bet. Their role, however, is found to be negligible. In two other treatments, a Trustee makes the return decision. The Trustor has either no information about the trustworthiness of the Trustee, or he receives social history information about the typical observed behavioral pattern in a Trustees' population. Houser et al. (2010) find that subjects' lottery risk preferences, as measured by Holt and Laury (2002), explain behavior in their computerized risk treatments, but not in the interpersonal trust treatments. They state, "this finding does not necessarily imply that risk attitudes are unimportant to trusting decisions, but it does suggest that, to the extent that risk attitudes do modulate trusting decisions, the mechanism remains to be discovered".

Both Bohnet and Zeckhauser (2004) and Houser et al. (2010) attempt to align the measurement of risk preferences with uncertainty in the Trust Game. Risk is simulated via information about the distribution of Trustees' decisions from previous rounds (Bohnet and Zeckhauser, 2004), or other experiments (Houser et al., 2010). Therefore, the information provided to Trustors on which basis they can assess Trustees' risk profile does not directly relate to the situation at hand and it might fail to induce purely objective risk.

In Bohnet and Zeckhauser (2004) participants' MAP was compared to a predetermined probability, P*, in both their decision problem (lottery) and the Trust Game. The value of P* in the decision problem was established by the fraction of Trustees who chose to reward trust in the Trust Game in the first two sessions. Participants are not told how this P* is determined, nor what its value is. As P* is unknown it is up to the participants to form a prior. The P* for the Trust Game, on the other hand, is determined in each session separately by Trustees' statements, before they actually decide, whether they would reciprocate if their matched partner would choose trust. This opens the possibility that participants interpreted the P* differently in the lottery and in the Trust Game. Also, participants remain uncertain whether the P* in the Trust Game is the correct description of the Trustees they interact with. In summary, the design does not fully induce objectively known risk in the trust decision.

In Houser et al. (2010), the probability distribution of reciprocity in both trust treatments is similar to the social history information from Berg et al. (1995). Participants knew that this information describes Trustee's choices in the past, and that it does not guarantee that it precisely reflects the decisions of Trustees in the current session. The social history provided to participants might not correspond to the actual probability distribution of trustworthiness in a given session, and subjects might be aware of this. This leaves room for Trustors to formulate alternative beliefs about trustworthiness of Trustees. Most importantly, this information does not fully remove the uncertainty about the trustworthiness of Trustees in the current session.

Thus, although both studies attempt to capture risk directly in a trust setting, they do not guarantee that the Trustors know the probability distribution of trustworthiness with certainty. The simple design presented in this paper generates such an environment, with Trustors acting upon an objective probability distribution of trustworthiness, which is both correct and payoff-dependent. We also use a within subject design to control, like Houser et al. (2010), for individual effect confounds due to individual heterogeneity.

The remainder of this paper is organized as follows. In the next section, we explain the experimental design and procedures. In Section 3 we present our results. Section 4 concludes.

Experimental design and procedures

The standard Trust Game

The STG that we study as a baseline builds on the Trust Game by Berg et al. (1995). We implement the game as follows. The first mover, Trustor, decides how much of her endowment E = 10 tokens (1 token = €0,50) to transfer to the second mover, the Trustee. Transfer $x \in \{0, 1, \ldots, 9, 10\}$ is multiplied by three before reaching the Trustee. Trustees on their behalf make a binary choice between either keeping the full amount or sending back half of the transferred tokens. We implement the game behind the veil of ignorance. All subjects make their decisions as a Trustor first and then as Trustee. They receive no feedback on decisions of others before providing complete information in the experiment. At the end of the experiment, one of these roles is assigned to each subject, and only the decisions in the assigned role are payoff-relevant for the subject.[11]

When taking their decision to honor trust, Trustees do not know whether a Trustor has sent money or not. Trustees make a binary choice between returning either half or nothing of the money in case of a transfer. Such a restricted Trustee strategy set is also used in, for example, Bohnet and Zeckauser (2004). This design ensures that Trustors choose a level of investment that exclusively stems from their inherent beliefs about Trustees' trustworthy behavior and prevents that the decision to trust is confounded by other motives, for example signaling or elicitation of positive reciprocity.[12]

The risky Trust Game

For the RTG we use the same setup as in the STG (see above) but implement the Conditional Information Lottery design developed by Bardsley (2000).[13] Trustors receive information that four Trustees have been randomly assigned to them, and that one of these four Trustees will be matched to them at random after the Trustees' decisions have been made. The Trustor is confronted with five possible scenarios: either none, one, two, three, or all four Trustee(s) may choose to return one half of the received amount. In the moment of decision-making, the

[11] If subjects engage in both roles (as Trustor and Trustee) this can have a negative impact on trustworthiness (Casari and Cason, 2009). To the best of our knowledge, no studies have shown any significant effects on trust (Johnson and Mislin, 2011), which is the main focus of our study.

[12] Servátka et al. (2007), for example, argue that Trustors may choose to invest a significant amount of their endowment in the hope that Trustees are more inclined to reciprocate, possibly due to guilt aversion.

[13] The Conditional Information Lottery offers all the benefits associated with deception in experiments, without actually deceiving anyone. The deceptive scenarios of designs, which use deceit, are replaced with scenarios, each of which, from a subject's viewpoint, has a chance of being true (Bardsley, 2000).

Trustor does not know which of these five possible scenarios will materialize.

For each of the five possible scenarios, we ask the Trustor to choose an amount that she wants to transfer to the Trustee that will be eventually randomly matched to her. Thus, Trustors in the RTG make five decisions, x_0, x_1, x_2, x_3 and x_4, where x_i, i=0,1,…,4, denotes the payoff-relevant transfer in case the group of four Trustees assigned to the Trustor contains i trustworthy Trustees. Allowing Trustors to condition their transfer in the RTG on all possible scenarios of trustworthiness that may occur, transforms the trust decision into a decision under risk with objectively known probabilities of Trustees' trustworthiness (in our case probabilities are 0, 0.25, 0.5, 0.75, and 1).

At the end of the experiment, the actual distribution of trustworthiness in the group of four Trustees will determine the payoff-relevant scenario for the Trustor. The Trustor's specific transfer in the materialized scenario of trustworthiness is randomly matched to one of the four Trustees assigned to him. The return decision made by this Trustee subsequently determines the monetary outcome of the randomly paired Trustor and Trustee.

For comparability reasons, we use the same matching procedure in the STG. Each Trustor is assigned to four Trustees, and one of the four Trustees is randomly selected as the payoff-relevant Trustee for the Trustor. In the STG, as explained in the previous section, the Trustor cannot condition the transfer on the trustworthiness of these four Trustees. Hence, the only difference between both Trust Games is that Trustors have objective probabilities about the trustworthiness of the Trustees in the RTG but not in the STG.

Risk preference measures

We elicit subjects' *lottery risk preferences* with a standard lottery setup (Holt and Laury, 2002). In this lottery risk task subjects make a sequence of 10 choices between two lotteries with changing probabilities of given outcomes. Subjects' lottery risk preferences are measured as the (last) point where a subject switches from option A, the less risky lottery, to option B, the more risky lottery (Holt and

Laury, 2002).[14] At the end of the experiment one of the 10 choices between option A and B is randomly drawn and the chosen lottery (A or B) is then played out with another random draw by a mechanistic random device (the computer).

For all subjects, we also estimate their *RTG risk preferences* by using their decisions in the five conditional scenarios in the RTG. The expected utility of a Trustor transferring x_i from an initial endowment (E) in a scenario with a fraction of p trustworthy Trustees (p= $\frac{i}{4}$), who return half of the tripled transfer, is given by:

$$EU(x_i) = p \cdot U\left(E - x_i + \frac{3}{2}x_i\right) + (1-p) \cdot U(E - x_i) \tag{1}$$

We assume the functional form of the Trustor's utility function to come from the family of constant relative risk aversion functions: $U(w){=}W^{\alpha}$ (see, e.g., Holt and Laury, 2002; Wakker, 2008). The first order conditions of the Trustor's expected utility maximization imply:

$$ln\frac{p}{2(1-p)} = (\alpha - 1)[ln(E - x_i) - ln\left(E + \frac{1}{2}x_i\right)] \tag{2}$$

The parameter α is estimated by means of an ordinary least square estimation for each subject separately, and we use it as our measure of interest for RTG risk preferences.

Experimental procedure

The experiments were conducted at ELSE (Experimental Laboratory for Sociology and Economics) at the University of Utrecht with 92 students (49 females and 43 males). The experiments were computerized using the software z-Tree (Fischbacher, 2007). At the end of each session, subjects were paid, in cash and in private, €11.50 on average for a session lasting about one hour.

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[14] Only four subjects switch more than once from the safer to the more risky lottery. The results we report later do not change if we drop subjects who switch more than once.

In the experiment, we control for individual heterogeneity by implementing a within-subject design. Subjects submit their decisions in two blocks. One block contained both versions of the Trust Game, the STG and RTG. Another block contained the measurement of lottery risk and some other incentivized auxiliary measures[15]. We balance the order of the Trust Games (RTG before or after the STG) in the Trust Game block, as well as the order of the two blocks themselves.

In the Trust Games, subjects always submit their decision in the role of a Trustor first, and only then in the role of a Trustee. All subjects received the same set of instructions and were aware of the fact that they had to submit choices for both roles in the Trust Game, and that payment in the Trust Game would depend on one role only. We also administered a non-incentivized post-experimental questionnaire.

All decisions were one-shot and we delayed any feedback about the decision of others and the outcomes of the randomization devices until the end of the experiment. The instructions for all tasks can be found in the Appendix.

Experimental results

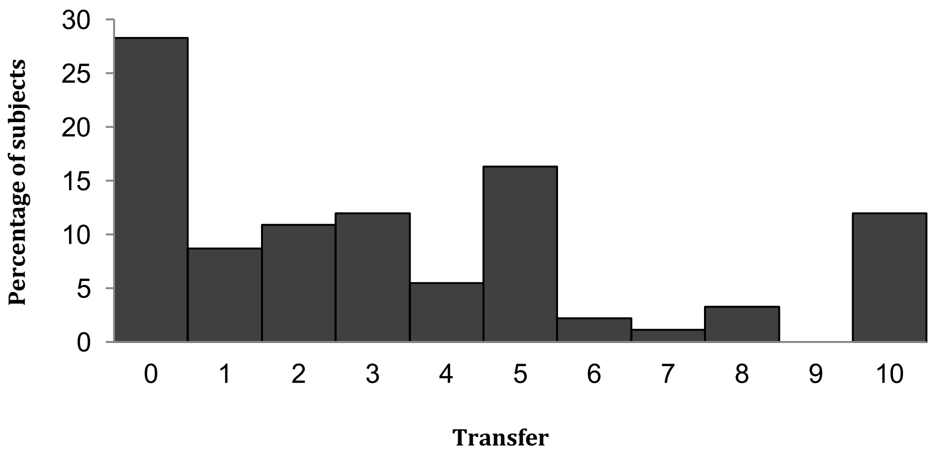
We first show descriptive statistics on Trustors' decisions in the STG and RTG, as well as lottery risk preferences and RTG risk preferences. Figure 1 reports the distribution of transfer decisions in the STG. The transfer distribution reveals the common peaks at the extreme transfers, as well as a considerable mass of transfers between zero and half of the endowment. The average transfer is 3.6 out of maximum 10 tokens, which is lower than the average in Berg et al. (1995), but well within the bounds of previously reported trusting decisions (Johnson and Mislin, 2011).

Figure 2 shows the transfers of Trustors for all scenarios in the RTG. As expected, the transfers increase in the number of trustworthy Trustees in a group. Average transfers in scenarios with 0, 1,...,4

[15] We measured social preferences via a standard social value orientation task (Liebrand, 1984) and lottery ambiguity preferences (Fox and Tversky, 1995). Lastly, we also asked which scenario from the RTG participants thought to be most likely. The results reported in this paper remain intact when we control for any combination of these additional measurements (See Appendix).

trustworthy Trustees per group are 1.02, 1.83, 3.45, 6.28 and 8.59 tokens, respectively.[16] The transfer of a risk-neutral Trustor in RTG would form a step-function with a transfer of 0 in scenarios with 0, 1, or 2 trustworthy Trustees and transfer of all tokens in scenarios with 3 or 4 trustworthy Trustees. The corresponding value of the parameter α for the constant relative risk aversion utility function is 0.656.

Figure 1: Distribution of transfers in the STG



[16] We also observe that about 30% of subjects transfer more than zero in the scenario with zero trustworthy Trustees. These positive transfers may reflect mistakes, warm glow from investing, or even belief that one can beat the odds even when this contradicts the available information (Andreoni and Miller, 2002; Ortmann et al., 2000). Most of these subjects transfer one or two units only, suggesting that some motivation rather than misunderstanding or noise guide such seemingly irrational transfers. At the other extreme, most of the subjects transfer the whole endowment when the probability to meet a trustworthy Trustee is equal to one. Here, the omission to transfer the whole endowment, next to mistakes, may be explained by competitive social preferences because any transfer below 10 creates a payoff disparity to the advantage of the Trustor.

Figure 2: Distribution of transfers in the RTG, for each scenario

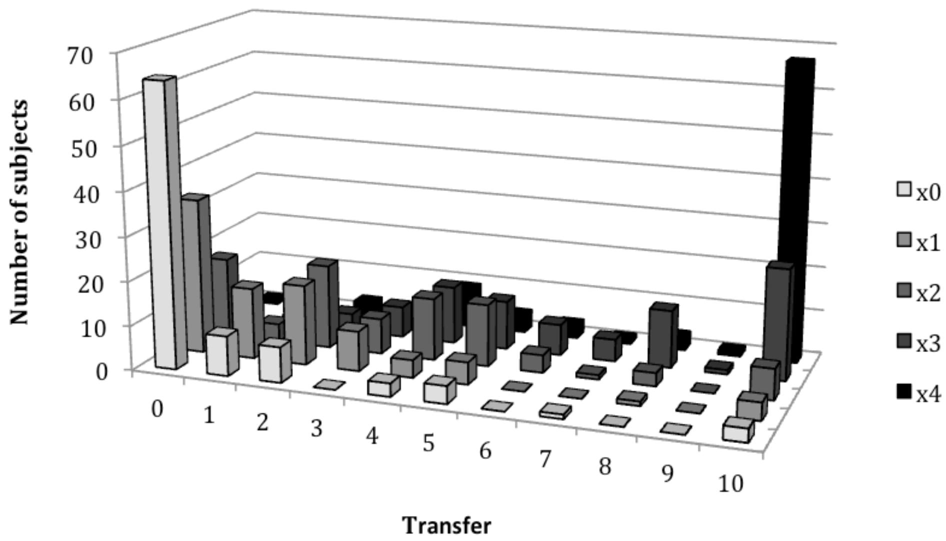


Table 1 reports the estimates for parameter α in equation 2 above, which measures subjects' risk preferences in the RTG. There are 8 participants with value α=0.656, corresponding to risk-neutral behavior. However, the majority of participants (n=64) are risk averse in the RTG.[17] As Table 1 shows, the RTG risk preferences range from a minimum of -18.529 (one extreme outlier) to a maximum of 2, with a mean of -0.278 and a median of 0.378. Both of the latter are well below risk neutrality.

[17] As a control measure, we analyze transfer decisions in scenario x_3 separately. In this scenario participants should transfer the whole endowment or at least much more compared to previous scenarios. The transfer in x_3 is highly correlated with the parameter α, elicited from all scenarios in the RTG.

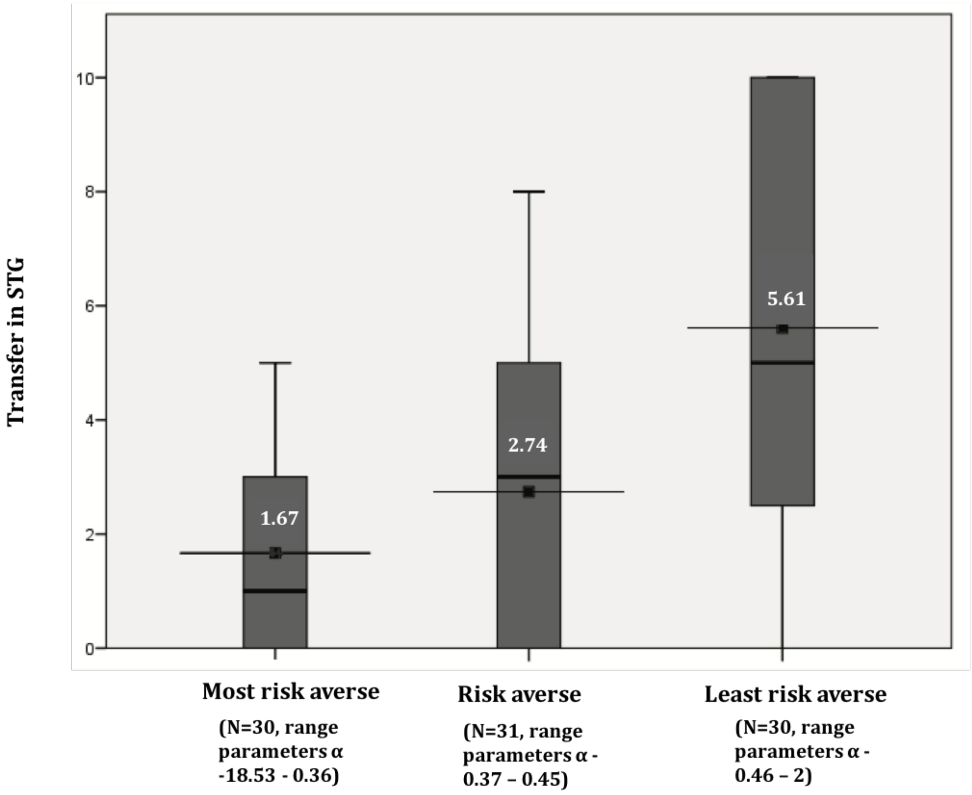
Table 1: RTG risk preferences	
Descriptives	Parameter α
Minimum	- 18.529
q 0.25	0.354
Median	0.378
q 0.75	0.656
Maximum	2
Mean	- 0.278
Standard deviation	2.416

Table 2 provides descriptive statistics for risk preferences elicited with the Holt and Laury (2002) lottery task. A risk neutral subject would switch to Option B, the more risky lottery, after having chosen Option A four times. We find a mean switching point of 5.82, which indicates that our subjects are risk averse, on average, in the lottery task. Compared to Holt and Laury (2002) our subjects are slightly more risk averse as they report a mean switching point of 5.2. Our mean switching point, however, is well in line with previously reported figures. Houser et al. (2010), for instance, report a mean switching point of 5.86.

Table 2: Lottery risk preferences		
Number of safe choices	Total (N=92)	Holt and Laury
0-1	0.00 (0)	0.01
2	0.01 (1)	0.01
3	0.01 (1)	0.06
4	0.16 (15)	0.26
5	0.16 (15)	0.26
6	0.25 (32)	0.23
7	0.27 (25)	0.13
8	0.00 (0)	0.03
9-10	0.03 (3)	0.01
Mean	5.82	5.2

Having described the most important data, we now move to bivariate analyses on risk and trust. Figure 3 reports the relationship between RTG risk preferences and trusting behavior in the STG. For visualization purposes we split the scores for risk preferences elicited from the RTG in three equally sized categories, ranging from risk averse to least risk averse. Subjects who are least risk averse send, on average, nearly 4 tokens more in the STG compared to subjects who are most risk averse.

Figure 3: Relating risk preferences measured in RTG and transfer in the STG



A Jonckheere-Terpstra test rejects the Null that there are no systematic relationships among the medians of the three different categories, in support of the alternative that the medians are ordered from most risk-averse (lowest) to least risk-averse (highest) ($p<0.001$).

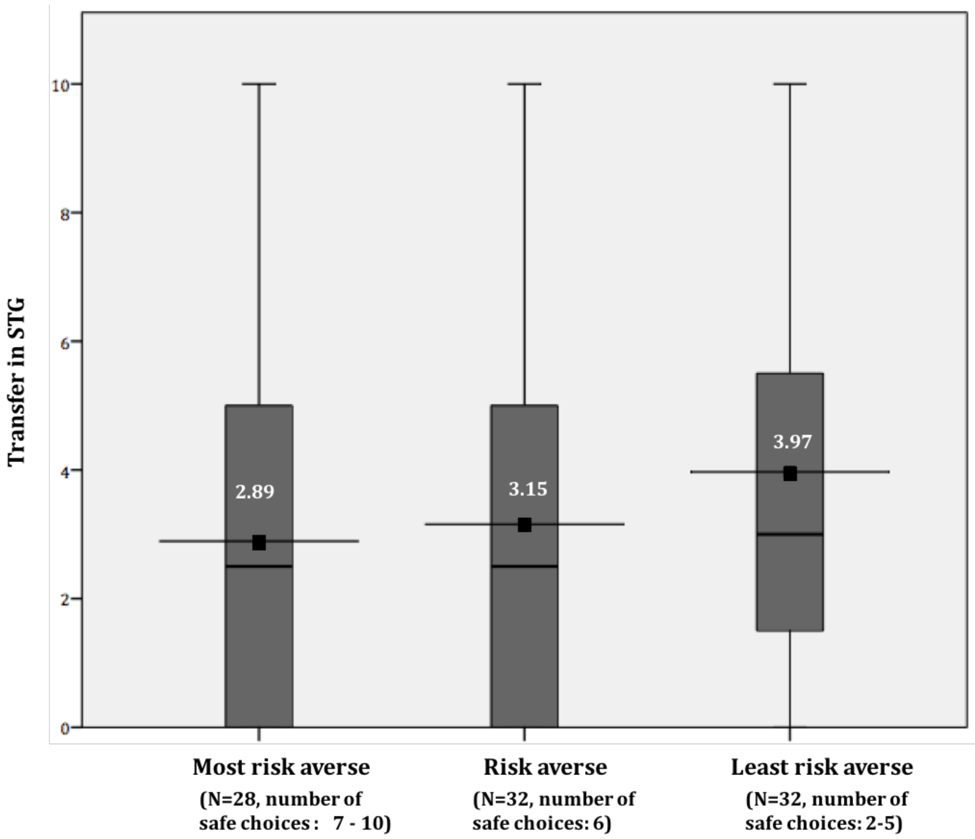
Moreover, a Pearson product-moment correlation test confirms that subjects' individual RTG risk preference measures are positively and statistically significantly correlated with corresponding transfers in the STG ($r=0.242$; $p<.05$). This is also confirmed by Kendall's tau rank correlation coefficient between RTG risk preferences and STG transfers, which is $\tau=0.341$ with $p<.01$. *Hence, as a first result, we find a strong positive bivariate relationship between risk preferences measured in a trust setting (RTG) and trusting behavior in the STG.*

Figure 4 shows the relationship between lottery risk preferences and trusting behavior in the STG. To enable a comparison with Figure 3 we split the lottery risk preferences into three equally sized categories ranging from most risk averse to least risk averse.[18]

Although the mean transfer in the STG slightly increases from 2.85 to 3.15 and to 3.97 as we move into less risk averse categories, the bivariate relationship between lottery risk and trust is not statistically significant. A Jonckheere-Terpstra test cannot reject the Null that there are no systematic relationships among the medians of the three different categories ($p=0.220$). Also, the Pearson's correlation coefficient ($r=0.151$; $p=0.15$) and Kendall's tau rank correlation coefficient ($\tau= 0.114$; $p=0.17$) cannot reject that subjects' individual lottery risk preferences are uncorrelated with transfers in the STG. *Hence, as a second result, we find no bivariate relationship between lottery risk preferences and trusting behavior in the STG.*

[18] If we apply the categorization based on Holt and Laury (2002), we find that, on average, risk averse participants transfer 2 tokens, risk neutral participants 4.73 tokens and risk seeking participants 3.12 tokens.

Figure 4: Lottery risk preferences and transfer in the STG



As the RTG risk preferences of Trustors predict transfers in the STG but lottery risk preferences do not, we expect to find no direct correlation between the two risk measures. Indeed, the Pearson correlation coefficient for the two risk measurements is not statistically significant (r=-0.10; p=0.921). This also applies to Kendall's tau rank correlation coefficient (τ= 0.081; p=0.301), which rejects any significant relationship and suggests that the two risk preference measurements are orthogonal. *Hence, as a third result, we find no bivariate relationship between lottery risk preferences and RTG risk preferences.*

Finally, we support our bivariate findings with multivariate estimations where we use the transfers in the STG as dependent variable and both risk measures as independent variables. Table 3 presents the results of OLS regression models where we control for demographic variables and session fixed effects.

Table 3: OLS regression models explaining transfer in STG.

Independent variables:	**Model 1**	**Model 2**	**Model 3**
RTG risk preferences	0.303*** (0.098)	-	0.316*** (0.091)
Lottery risk preferences	-	0.367 (0.265)	0.405 (0.273)
Gender	-0.048 (0.817)	0.084 (0.857)	0.236 (0.834)
Economics major	-0.001 (0.844)	-0.008 (0.820)	-0.123 (0.808)
Session 1	0.291 (1.209)	0.387 (1.243)	0.121 (1.192)
Session 2	-2.029** (1.016)	-1.868* (1.047)	-2.137** (0.970)
Session 3	0.595 (1.066)	1.080 (1.058)	0.627 (1.039)
Session 4	0.121 (1.133)	0.177 (1.155)	-0.288 (1.083)
Session 5	-0.197 (1.301)	0.128 (1.326)	-0.350 (1.274)
Constant	3.729 (0.890)	1.855 (1.326)	2.053 (1.436)
N	92	92	92
	(8, 83)	(8, 83)	(9, 82)
F test	2.96	1.67	3.00
Prob. > F	0.0057	0.1168	0.0038
R - squared	0.1363	0.1085	0.1596

The estimation results in Table 3 clearly show that risk preferences stemming from the RTG remain economically and statistically significant predictors of trust. RTG risk preferences are an important predictor of trusting behavior in the STG with or without lottery risk preferences as simultaneous independent variable (see Model 1 and 3). In contrast, as expected, we find no relation between lottery risk preferences and transfers in the STG, neither individually (Model 2) nor in combination with RTG risk preferences (Model 3). *Hence, as a fourth and most prominent result, we find an economically and statistically significant relationship in multivariate regressions between risk preferences and trusting behavior, provided that risk preferences are measured in a trust setting and not with a lottery setup.*

We conducted several robustness checks to analyze the validity of the above results. First, we ran regression models in which we included all auxiliary measures elicited in the experiment (lottery ambiguity preferences, social preferences and Trustor's beliefs). In line with previous studies (Dufwenberg and Gneezy, 2000) we find that Trustors' beliefs about Trustees' return decisions play a role when explaining the variation of transfers in the STG. We also ran regression models in which we excluded all subjects from the regression analyses, who transferred more than zero (less than ten) tokens in the scenarios with zero (with four) trustworthy Trustees. This resulted in a smaller sample of 51 subjects. In all these models, RTG risk preferences remain highly significant while lottery risk preferences fail to be meaningful predictors of trust.[19]

Conclusion

In this paper we propose a measure of risk preferences relevant for decisions of Trustors in the Trust Game. We present a new design, the RTG, which fully aligns the context for the measurement of risk preferences with the context of the Trust Game. We show that subjects' risk preferences, measured in the RTG, explain transfers in the standard. In contrast, and in line with previous studies, our results also show that subjects' lottery risk preferences are not able to explain variations in transfers in the Trust Game. This suggests that subjects perceive the same objective risk in trusting differently from the risk in a lottery. In fact, we find that risk preferences that are elicited in a trust setting (in our RTG) are completely uncorrelated with risk preferences

[19] All results are available in the Appendix.

elicited with the well-known Holt and Laury (2002) lottery design. Subjects' risk preferences are context dependent, and the risk measure obtained in the lottery context does not sufficiently capture the risk that subjects perceive in the trust decisions.

Our findings relate to recent research on sources of risk (Weber et al., 2002; Abdellaoui et al., 2011; L'Haridon et al., 2013). Rather than describing a risky decision purely in terms of the set of states and objectively known probabilities of these states, the sources of risk take into account that human decision-makers process objectively known probabilities in a context-dependent way. This notion is supported by recent neurocognitive studies, which propose that the origins of source dependence in risk processing can be found in human neurobiology. They highlight the importance of a brain circuit that specifically underlies the representation of other's beliefs and intentions (Saxe, 2006; Behrens et al., 2008; 2009; Hampton et al., 2008). The dissociation in processing of risks from social and non-social sources was also linked to neuroanatomy. Brain signals from the regions processing social risk are strongly interconnected with other brain regions involved with the processing of emotions and facial expression (Van Hoesen et al., 1993). Closely related to our research, Lauharatanahirun et al. (2011) observe that risky decisions in a social vs. non-social setup recruit different brain regions of interest, giving further support to the source perspective of risk decisions of human decision-makers.

Coming back to the question we started this paper with – can trust in the STG be explained by a person's risk preferences – our results suggest the following answer: Yes, it can, but only if we align the measurement of risk preferences to the source of uncertainty a person faces in trust decisions.

Chapter 3

Social sources of uncertainty: an fMRI study[20]

Introduction

Decision-making under situations of uncertainty is an everyday feature in life. For instance, your best friend just lost her job and asks you to lend him money. In this case, we assume you know your friend well and are therefore perhaps 95% sure of your belief estimation concerning the likelihood of repayment. But, what if a stranger approaches you and also asks you to lend him money after a similar job loss? In the latter situation, without knowing anything about this stranger it is very difficult to assess an accurate probability of repayment. These differences illustrate the distinction between the concepts of risk and ambiguity (Wakker, 2010) as two different *types* of uncertainty. Most of our decisions are ambiguous, as the majority of events cannot be fully described by exact probability estimation. In addition to the distinction between risk and ambiguity as types of uncertainty, the example above also highlights an additional feature of DMUU, namely, its *source*. The uncertainty mentioned above has a *social source* as it stems from the actions of another human being. As we move through society we are constantly interacting with others, and indeed many of the uncertainties we face on a daily basis are related to the behavior of others (Trautmann and Vieider, 2011).

Despite the involvement of the intentions of other people in our risky and ambiguous choices, most experimental studies on DMUU primarily focus on lottery contexts. The majority of experimental studies still use a setup that was implemented in an influential

[20] This chapter is based on a joint paper with Alan Sanfey, Jana Vyrastekova, and Utz Weitzel, Social Sources of uncertainty: an fMRI study, 2015, under review.

experiment by Daniel Ellsberg in 1961 (see BOX 1 of the Introduction). The predominant finding that participants shy away from ambiguity in this experiment contradicts SEU and has been termed ambiguity aversion (Trautmann and van de Kuilen, 2013).

In this Chapter we investigate how preferences for risk and ambiguity are affected when the outcome is determined by the choice of another person (social source), as compared to when the outcomes hinges on the draw of a marble from a standard Ellsberg urn (non-social source). Although economic studies do acknowledge different sources of uncertainty, these different sources of uncertainty to date have only been applied in non-social settings (Abdellaoui et al., 2011; Hsu et al., 2011). For instance, these sources of uncertainty occur due to meteorological conditions (betting on the temperature of a city in a foreign country) or a process beyond the control of the decision-maker (betting on the trajectory of a stock on a foreign stock exchange), but do not stem from a conscious choice made by another human being. Therefore, in this Chapter we differentiate between uncertainties that stem from a lottery, state uncertainty versus uncertainty that arises due to the actions of other people, strategic uncertainty (Houser et al., 2010).

There are several reasons as to why attitudes towards social and non-social sources of uncertainty may differ. Losing money to another decision-maker instead of to a random mechanistic device can be perceived as a conscious betrayal, and work in experimental economics suggests that people experience betrayal aversion (Bohnet and Zeckhauser, 2004; Aimone and Houser, 2012). This rationale proposes that participants exhibit greater risk aversion in a social setting as compared to a non-social context because they dislike when another player consciously decides not to reciprocate a positive action, thus 'betraying' the decision-maker. Betrayal aversion might be due to intentionality (Falk and Fischbacher, 2006), as clearly a mechanistic random device such as a die or slot machine cannot make a conscious choice in (dis)honoring risk-taking behavior. Alternatively, when interacting with another decision-maker results in a loss, one may perceive this more as a 'failure signal' in correctly assessing the social situation. On the other hand, losing to a random mechanistic device may be more readily perceived as simply bad luck (Trautmann et al., 2008).

As previous studies have demonstrated the role of these social influences on either risk (Bohnet and Zeckhauser, 2004; Houser et al., 2010; Trautmann and Vieider, 2011) or ambiguity (Aimone and Houser, 2012; Trautmann et al., 2008) separately, w take account of both types of uncertainty in this Chapter. We aim to understand why decision-makers might differentiate between social and non-social sources of risk and ambiguity. We conducted an fMRI experiment in order to study the neural mechanisms underlying social and non-social of uncertainty.

Several previous fMRI studies have explored neural differences when people interact with humans instead of computers (McCabe et al., 2001; Delgado et al., 2005; Kosfeld et al., 2005; Amodio et al., 2006; Saxe et al., 2006; Behrens et al., 2008; 2009). Some of these studies use a standard Trust Game setup (Berg et al., 1995) to evoke the social interaction. In this game there are two players, known respectively as the Trustor and Trustee. The Trustor is endowed with 10 tokens and can choose to invest some of these tokens with the Trustee. The experimenter then (standardly) triples the investment before it reaches the Trustee. The Trustee can return some of this tripled investment to the Trustor, but is also free to keep the whole investment to himself. The Trustor needs to offset the possibility of receiving back a multiplier of her investment with the risk of losing some, or even all, of this investment. Trust is quantified as the amount a Trustor invests with a Trustee.

Typical comparisons of decision-makers' behavior in the Trust Game to a non-social setting go along these lines: subjects were matched with either a human or computer counterpart. When subjects played with the computer they were told that it would play a fixed probabilistic strategy of X percent of returning half and (100-X percent) of returning none of the Trustor's investment. In the social context, participants did not receive any such probabilistic information regarding the reciprocation rate of the Trustee (McCabe et al., 2001; Kosfeld et al., 2005). This procedure obviously introduces some confounds regarding the type of uncertainty by comparing lottery choices under risk with trust decisions under ambiguity. These methods introduce another aspect beyond comparing social to non-social interactions, namely the distinction between both types of uncertainty, and make it difficult to assess the true effect of the source of uncertainty.

Other fMRI studies have focused on types of uncertainty, though not in concert with social sources (Hsu et al., 2005; Huettel et al., 2006; Bach et al., 2009; 2011; Levy et al., 2010; Rustichini et al., 2005). These latter studies consistently show evidence of ambiguity aversion in lottery contexts, but offer different explanations as to the neural mechanisms underlying this behavioral pattern. One group emphasizes the role of the amygdala and the orbitofrontal cortex, explaining ambiguity aversion in terms of fear of uncertainty (Hsu et al., 2005). However, another group finds brain regions such as the inferior frontal gyrus (IFG), the posterior parietal cortex, precuneus, middle temporal gyrus, and the superior and inferior parietal lobule (Huettel et al., 2006; Bach et al., 2011), and explain ambiguity aversion as a more complex expected value calculation where one is integrating multiple possible subjective probability distributions in order to resolve ambiguity. Importantly, all of these studies use lotteries to evoke uncertainty.

Therefore, our goal here is to examine the relationship between the source of uncertainty (social vs. non-social) and the type of uncertainty (risk vs. ambiguity), in a design that allows for dissociation between these aspects, as well as exploring the interaction between them. This multi-faceted approach allows us to investigate if the source of uncertainty itself affects the neural correlates related to ambiguity preferences. In addition, this approach allows us to shed light on the different explanations given thus far to the underlying mechanism of ambiguity aversion.

In this study we also take account of individual beliefs as we expect that individual differences in beliefs might affect both sources and types of uncertainty. Namely, previous work has highlighted the role of individual beliefs in trust decisions (Chang et al., 2011). Also, ambiguity preferences are influenced by the underlying likelihood. Decision-makers express more ambiguity seeking behavior when they consider low likelihood events, but express more ambiguity aversion for high likelihood events (Abdellaoui et al., 2011; Kocher et al., 2015). Therefore we elicited decision-makers' beliefs in our experiment in order to investigate individual differences in ambiguity preferences.

Two existing fMRI studies have conceptual similarities to our approach. Lauharatanahirum et al. (2012) looked at the difference in neural activity between social and lottery risk. Participants in their study could either invest nothing (sure option) or their complete endowment (risky choice). In the social condition the probabilistic information stems from actual decisions of Trustees taken from a previous behavioral session. In the non-social condition, the distribution of outcomes in a lottery was matched to have the same mean, variance, and skewness. Their findings show that activation in the left amygdala, based on an anatomical region of interest (ROI)[21], correlates with a three-way interaction of group (more risk averse in social context versus lottery context) times condition (social versus non-social) times choice (risky option versus sure option).

Aimone et al. (2014) also investigated social and non-social sources, but they exclusively focus on ambiguity by not providing any probabilistic information. In their setup, players can either indicate trust by investing all their tokens, or no trust by investing nothing. In the trust treatments the Trustor's choice was randomly paired with a Trustee who previously chose to either reciprocate or betray. In the non-social context, the investor's choice was also randomly paired with a Trustee, but a computer mediated in such a way that investors could not identify the potential betrayal by the Trustee. The main focus of their study is on betrayal aversion, and their behavioral results suggest that significantly more trust was displayed when the likelihood of betrayal aversion was removed in the computer-mediated trials. They find higher activation in the right anterior and posterior insular cortex when subjects decide to trust in the trust treatment compared to the computer-mediated treatment. Aimone et al. (2014) interpret activation in the insula to reflect the heightened negative state associated with betrayal aversion.

Whereas the aforementioned studies compare neural differences between social and non-social risk (Lauharatanahirum et al., 2012), and social and non-social uncertainty (Aimone et al., 2014), our study incorporates the full spectrum of uncertainty by incorporating both risk

[21] A common approach to the analysis of fMRI data involves the extraction of signal from specified regions of interest (Poldrack, 2007).

and ambiguity in a social and lottery domain, additionally allowing us to examine the relationship between these contexts. Moreover, we take individual beliefs into account, which enables us to study individual differences in social and non-social ambiguity preferences.

Participants will undergo fMRI as we examine participants' attitude towards both risk and ambiguity, within the framework of both a social and non-social source. In the social context we adapted the standard Trust Game (Berg et al., 1995), as described previously, to evoke strategic uncertainty whereby the social source of uncertainty stems from the actions of the Trustee. Here, participants can choose between six discrete investment amounts: 0, 2, 4, 6, 8 or 10 tokens (tokens are exchanged for a monetary value at the end of the experiment). Participants' investment is tripled by the experimenter and is either placed in the lottery, or is sent to another, real, person who has previously made a return choice in the role of Trustee in the Trust Game. For the non-social context we used the typical Ellsberg lottery setup.

Importantly, and as an additional novel feature of the design, we take individual beliefs into account in order to have a fair comparison between our risk and ambiguous settings. We matched participants' beliefs concerning Trustee's reciprocity levels with an equal underlying likelihood in the lottery context. This enables us to look at individual differences in ambiguity preferences as modulated by participants' individual beliefs.

Based on fMRI and behavioral insights discussed above, we hypothesize that people will be more sensitive to the distinction between risk and ambiguity in the social context than in the lottery context. Therefore we expect ambiguity aversion to be more prominent in the social context. Our neuroimaging data will allow us to investigate the underlying neural mechanisms that affect social ambiguity, and if they differ from previous fMRI findings on ambiguity evoked by a standard lottery.

Experimental design and procedures

Participants

Twenty-six participants (mean age = 22 years, 50% female) signed up for this study via the online recruitment system SONA of the Donders Institute for Brain, Cognition and Behaviour. They were pre-screened for any behavioral and health related abnormalities via an online questionnaire, and we also provided participants with online information regarding the MRI scanner and safety restrictions (see BOX 3 in Introduction for distinction between fMRI and MRI). Finally, we contacted our participants by phone to fill out the MRI safety checklist. The local ethical committee approved this study.

We excluded four participants from our sample prior to analysis. One was removed because the head coil was not applied correctly, one because they did not believe that there was real human interaction in the social condition, another because they chose the exact same investment for all trials during the experiment, and finally one participant had extreme choices which differed more than two standard deviations from mean responses. The analyses reported here are therefore based on twenty-two participants (mean age = 22, 12 females and 10 males).

Experimental design

Participants made investment choices (described as 'transfer' for participants) in four different treatments: a risky Trust Game (RTG), an ambiguous Trust Game (ATG), a risky lottery (RLOT) and an ambiguous lottery (ALOT). Participants could choose between six different investment options: 0, 2, 4, 6, 8 or 10 tokens. This investment was tripled by the experimenter, and was sent to either a (human) receiver in the Trust Game or invested in the lottery.

In the social context, participants made investment choices in the role of sender (Trustor in the original Trust Game), with this investment then paired with one receiver (Trustee in the original Trust Game) randomly drawn from a group of nine receivers. In a pre-session, all receivers previously made a choice to either reciprocate (send back half of the received tokens) or keep an investment if paired with a sender who transferred a positive amount. In the RTG the sender received information about the composition of nine receivers, that is, how many of the nine receivers chose to reciprocate and how many did not, whereas in the ATG they did not receive this information.

In the non-social context, marbles in a lottery replaced the receivers. The lottery always consisted of nine marbles, and was of two different types. In RLOT each of the nine marbles has a different color, whereas in ALOT the lottery is made up of an unknown composition of the nine available colors. Essentially any set of combination of nine colors is possible in the ALOT (thus 9^9 combinations). As in the Trust Game, participants can receive back either half of the tripled investment or lose the entire investment. In both the RLOT and ALOT participants receive information as to which of the nine colors are 'winning' colors. As the ALOT is an urn filled with nine marbles in an unknown color composition, receiving information regarding the number of winning colors is not the same as the objective probability seen in the RLOT.

In our design, it is important that we control for individual beliefs. In the social context, participants have naturally occurring prior beliefs about the reciprocity behavior of receivers. Before participants were placed in the MRI scanner we elicited these individual beliefs by asking participants how many of nine random receivers they thought would likely reciprocate their investment. This prediction was then used to align individual beliefs in the social context by creating a similar underlying likelihood of drawing a winning colored marble in the lottery. Participants received a greater number of RLOT and RTG trials with objective probabilities that matched their individual social prediction (see Figure 5).

To match for the fact that there is a second player in the two Trust Games, we introduced a dummy player to the lottery conditions. This dummy player did not make any choice, but acted as a recipient. Therefore, the dummy player received the exact same outcome, as the receiver would have earned in the Trust Game, but based on the lottery outcome. If a winning marble was drawn in the lottery, half of the tripled investment went to our fMRI participant and the other half to the dummy recipient. If the lottery resulted in a losing colored marble, the tripled investment was directly handed over to the recipient. By implementing this feature, we controlled for social preferences – for example, warm glow from investing – as a potential confounding factor (Houser et al., 2010). Importantly, the dummy player is not one of the receivers. These participants were recruited after an experiment at the Nijmegen School of Management decision laboratory, and were asked if they wanted to be a counterpart player in an upcoming fMRI experiment.

Experimental procedures

All behavioral sessions in this study took place at the Nijmegen School of Management decision laboratory. Here we collected the receivers' decisions for the Trust Games and recruited dummy players to act as lottery recipients. The fMRI experiment took place at the Centre for Cognitive Neuroimaging at the Donders Institute for Brain, Cognition and Behavior.

No deception was used in this experiment. Participants were financially compensated based on their actual choices and the accuracy of their stated beliefs.

Receivers

In the social setting fMRI participants made choices as senders and these were randomly paired with a receiver. Receivers' choices were collected during a behavioral session several weeks prior to the fMRI study. Receivers could make two choices: to send back half of any amount of tokens received (between 0-10) or keep the transferred amounts for themselves. Importantly, receivers had to make their return choice unconditionally, not knowing if and how many tokens they would receive. This element in our design is crucial, as we want senders to make investment decisions based solely on their beliefs regarding receivers' reciprocity. In this way we ensure that the decision to invest is not confounded by other motives, for example signaling or the elicitation of positive reciprocity.

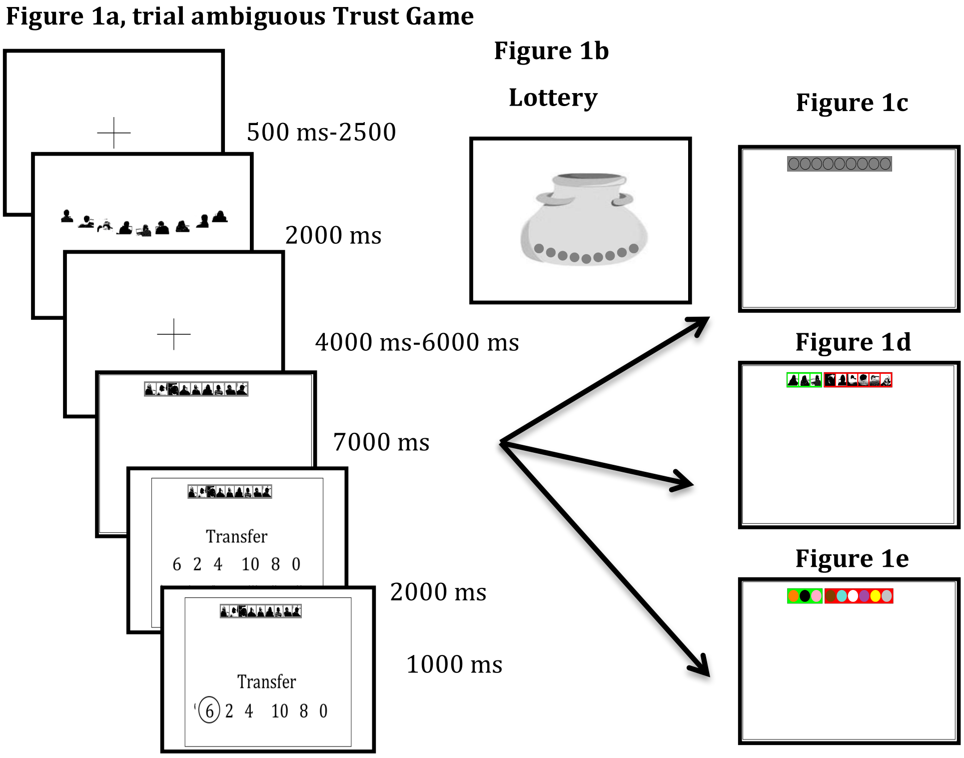
When receivers made their decisions in the decision laboratory, we videotaped the session and took pictures while they were seated behind a laptop. The pictures only show receivers' silhouettes in black and white and no facial features are shown. We asked for approval upfront, but indicated that we would explain the necessity of this material after they had made their decisions. We informed them about the upcoming fMRI experiment only after receivers had made their return decision.

We asked participants' approval to use their return choice as receiver with a participant who would play in the role of sender in an upcoming fMRI experiment. We also informed them that our fMRI participants would see the video material and the photo material. Lastly, we asked receivers to answer a questionnaire regarding some personal information, like gender, hobbies, and relationship status. All questionnaires were put together in a booklet and would be given to fMRI participants during the instructions. This was to ensure that the fMRI participants would believe that the interaction in the social context was really based upon an actual social choice of another person. Additionally, it ensured that all fMRI participants received the same information about the receivers. In the same week we collected receivers' choices, we also ran a behavioral session with senders. Therefore we could immediately incentivize receivers' decision-making by matching one receiver and sender, randomly drawn from each behavioral session.

fMRI experiment

One day prior to the fMRI session, the fMRI participants received an email and were instructed to fill in a color table. At this point in time they did not receive any information regarding the experiment, and were unaware which purpose their selected colors served. This color table enabled us to define each individual's selected colors in the lottery context. For every participant the winning colors in the RLOT scenarios were programmed and visually displayed according to the color table they themselves filled in. This procedure minimizes any suspicion participants might have had with regard to the composition of the ALOT (Wakker, 2010).

Figure 5: Overview experimental design



Each trial consists of six screens. Figure 1a is an example of a trial from the ATG. Fixation crosses are jittered. The second screen indicates the source of uncertainty. Nine silhouettes are displayed when participants are in a social context. Nine marbles are displayed when participants face a lottery context (Figure 1b). The fourth screen is the decision screen. They are instructed to decide how much to transfer here. As the six possible transfer options appear in a random order on the next screen, they are unable to prepare for a specific button press. In the ATG (Figure 1a) nine silhouettes on a grey background indicate that no information is given about the distribution of receivers that decided to send back half or keep the investment. To illustrate the tailor-made structure of our design, we assume a participant who believes three out of nine receivers will reciprocate. In the ALOT (Figure 1c) the participant receives instruction that three out of nine colors that can be used in any combination in this lottery are winning colors. In this way we align underlying subjective probabilities between the ATG and ALOT. In the risky trials we align individual's beliefs to objective probabilities. A participant who believes three out of nine receivers will reciprocate, will most often face a RTG, which is composed of three receivers (green background) that decided to send back half of any received investment versus six receivers (red background) that decided to keep their investment (Figure 1d). Finally, in the RLOT the urn is composed of all nine colors out of which three are winning colors (green background) and six are losing colors (red background) (Figure 1e).

On the day of scanning, participants received detailed instructions, had time to ask questions about the procedure, and were briefly tested as to their understanding of the tasks. On average participants took 75 minutes to complete the instructions. This also included the belief elicitation task. In the MRI scanner participants could make some practice choices, and could ask questions for clarification if necessary.

The fMRI task was presented using Psychtoolbox (Matlab). Participants saw two runs, with a break in between. The first run, where they made their decisions, is the focus of this paper. There were 96 trials in total, equally divided between Trust Game and lottery trials. There were 16 blocks in total. Each block consisted of six trials of either Trust Game or lottery decisions. Within each block both risky and ambiguous trials were presented in a random order.

In the risky trials participants were shown the objective probabilities that their investment would be returned before they chose to invest. As outlined above, the exact set of risky trials was tailored to each participant's belief regarding receivers' return choice in the ATG (Figure 5). In addition, we also had filler trials for other probabilities that did not match participants' beliefs. These trials were not included in the fMRI analyses. There were no filler trials in the ambiguity setup. The ALOT trials only consist of trials where the underlying likelihood to draw a marble that matches one of their selected colors is equal to their belief from the ATG.

Participants indicated their transfer decisions by pressing one of six buttons arrayed on two MRI compatible button boxes, which were placed on the participant's lap. The three transfer options on the left of the screen were linked to the left button box and the options of the right were linked to the right box. All participants reported no problems to indicate their choices via this procedure.

In the second run of this experiment the associated decision outcomes were presented. Results from this phase will be presented in Chapter four of this thesis.

Imaging procedures

Scanning was carried out on a 3-Tesla Siemens MRI system

(Magnetom Skyra). Functional MRI (fMRI) images were acquired using a 32-channel head coil, with a standard multi-echo imaging pulse T2*-weighted sequence (field of view = 224 mm, matrix = 64 × 64, repetition time (TR) = 2390 ms; echo times (TE) = 9.4 ms, 20.6 ms, 32.0 ms, 43.0 ms, 54.0 ms, flip angle = 90°, slice gap = 0.5 mm). Using a multi-echo sequence provides a better signal-to-noise ratio for brain areas susceptible to dropout, while allowing for scanning of the whole brain (Poser et al., 2006). One whole-brain volume consisted of thirty-one ascending slices (slice thickness = 3.0 mm, voxel size = 3.5 × 3.5 × 3.0 mm). For each participant we acquired a high-resolution anatomical T1-weighted image (MPRAGE; 192 slices; TR = 2300 ms, voxel size = 1 × 1 × 1 mm). We loosely taped participants' head to the coil within the scanner in order to limit movement during image acquisition.

fMRI preprocessing

fMRI data analysis was performed using SPM8 (Statistical Parametric Mapping; Wellcome Department, London, UK). Prior to preprocessing we combined and realigned the five read-outs acquired via the multi-echo sequence by using standard procedures described by Poser et al. (2006). The first 31 volumes, acquired prior to task initiation, were used to estimate the weighted echo time per voxel for optimal echo combination including allowing T1 equilibration effects. These 31 volumes were then discarded from the analysis (Poser et al., 2006). After echos were combined, preprocessing consisted of slice-timing to the middle slice, co-registration of the functional images to the anatomical images, segmentation of the functional and anatomical image, and normalization to the Montreal Neurological Institute (MNI) template using the segmentation parameters. Functional images were then smoothed with a Gaussian kernel of 8 mm full-width at half maximum (FWHM).

fMRI statistical analyses

To examine the neural mechanisms associated with both the source and type of uncertainty, we investigated the BOLD[22] response during trials on which participants decided how much to invest in

[22] Please see BOX 3 of the Introduction for an explanation of the BOLD response.

either another person or in a lottery. The main regressors for these trials are: decision screen of RTG, decision screen of ATG, decision screen of RLOT, and decision screen of ALOT (Figure 5, screens 4). The onsets are defined when the decision screen appears, and we include the onset of the button press on the subsequent screen in our generalized linear model GLM model.

These regressors were modeled with a canonical hemodynamic response function during a time-window of two seconds after the onset (duration). To account for residual variance, we also included the temporal derivatives of each regressor. The motion parameters from realignment, including its quadratic effect and first derivative (in total 18 motion parameters per individual), were included in the GLM.

A standard high-pass filter (cut-off 128 s) was used during the GLM analysis to account for possible slow-frequency drifts. Finally, a whole-brain second-level model was used to analyze group effects for the specified contrasts discussed in the results section (by means of a T-test). Individual beliefs were standardly included as a covariate. Statistical maps were corrected for multiple comparisons using whole-brain cluster correction with an initial threshold of $p < 0.001$ and a Family Wise Error corrected cluster threshold of $p < 0.05$. We only mention the number of voxels in clusters, which satisfy $p < 0.001$, uncorrected (> 10 voxels).

First, we tested the main effect of the type of uncertainty and the source of uncertainty by looking at the main contrast of ambiguous choice trials > risky choice trials and social choice trials > lottery choice trials, respectively. We explored the neural mechanisms of individuals' social and lottery ambiguity preferences in two ways. First, we added these individual preferences as covariates at the second level for the main contrast of ambiguous choices > risky choices. Second, we added participants' investment choices as parametric modulators to our GLM model and contrasted investment choices in the ATG > investment choices in the RTG (social ambiguity preferences), and investment choices in the ALOT > investment choices in the RLOT (lottery ambiguity preferences).

Results

Behavioral results

Beliefs influence investment choices

The average transfer in the ATG was 3.61 out of 10 tokens. This figure was lower than the average investment in the original Trust Game by Berg et al. (1995), but within the bounds of previously reported trusting decisions (Johnson and Mislin, 2011). Importantly, the average transfer in this fMRI study was very similar to mean investment amounts in a similar design we employed in a behavioral laboratory (Chapter 2 of this thesis).

Individual beliefs regarding receivers' reciprocity likelihoods varied substantially. Some participants indicated very low beliefs by stating that they expected that only two or three out of nine Trustees would reciprocate. On the other hand, some participants stated a belief that 6 of 9 Trustees would return their investment. Figure 6a illustrates that individual beliefs, which we elicited prior to decision-making, indeed positively correlated with the amount they subsequently invested in the ATG ($r=0.642$, $p=0.001$).

We also found a positive relationship between the amount of winning colors and participants' investment choices in the ALOT ($r=0.597$, $p=0.003$) (see Figure 6b). This indicated that participants attended to, and used, this information, which we provided during instructions before we placed them in an MRI scanner, to make investment decisions in the ALOT.

These results provided insight into DMUU: participants have expectations and use these to guide their choices. Moreover, in the design we employed, it is important that we showed this relationship. Any difference we find across our conditions is unlikely to be the result of a mismatch between subjective probabilities (based on participants' beliefs from the ATG) and objective probabilities in the risk treatments.

Social ambiguity aversion

We applied repeated measures ANOVA with the transfer decisions in the ATG, ALOT, RLOT and RTG as main variables. We controlled for individual beliefs by adding this as covariate. This analysis yielded a main effect of the type of uncertainty ($F(1,20)$ =

5.973, p=0.024). Participants invested less in the ambiguous treatments as compared to in the risk treatments, illustrating ambiguity aversion. When analyzing the pairwise comparisons, ambiguity aversion was only weakly significant in the social context ($F(1,20) = 3.680$, p=0.069), but not in the lottery context. There was no significant main effect of the source of uncertainty: investment choices across the lotteries and Trust Games did not differ (Figure 7).[23]

Figure 6 Beliefs and transfer in ATG and ALOT

Figure 6a

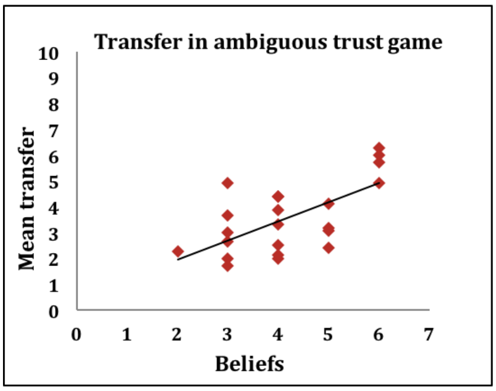
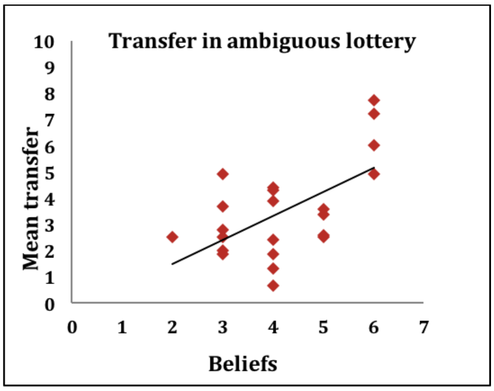


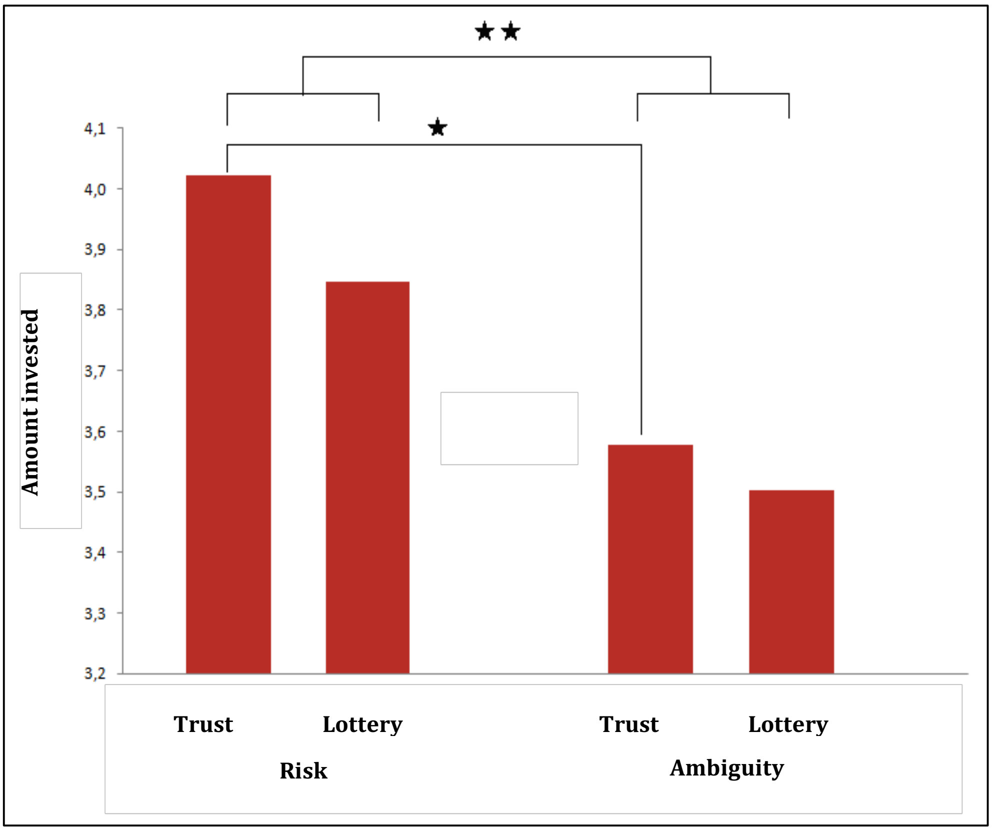
Figure 6b



Elicited beliefs influenced chosen transfer in the ATG. Based on individual beliefs, participants received a matching amount of winning colors in the ALOT. Particpants included this information, given during instructions prior to the experiment in the MRI scanner, as transfer positively increased as afunction of the amount of winning colors.

[23] In Chapter 2 of this thesis we concluded that risk preferences are context-dependent, as we found no correlation between amount invested in the RTG and risk preferences elicited with the Holt and Laury risk measurement. We used the Holt and Laury risk design as this was the primary elicitation technique to link individual risk in trusting. In the current Chapter we carefully designed a RTG and RLOT, which only difference is the source of risk. Based on this design we conclude that behavior across the RTG and RLOT is not significantly different, and is significantly correlated. We cannot make any comparisons between the current and previous Chapter with regard to social and non-social sources of ambiguity.

Figure 7: Amount invested across experimental conditions



On the Y-axis the mean amount invested is plotted for each different treatment. Each bar represents such a treatment. A main effect of the type of uncertainty is found: investment was significantly lower for ambiguity than for risk ($p < 0.05$). Only the pairwise comparison between the RTG and the ATG was weakly significant ($p < 0.1$).

Individual differences

Taking individual beliefs into account illustrates interesting individual differences in ambiguity preferences.

For each participant we calculated a normalized score of ambiguity preferences in both the social and non-social domain. We

subtracted the participant's average amount invested in the ATG from their average amount invested in the RTG, before normalizing:
Social ambiguity aversion = ((average transfer RTG – average transfer ATG)/ (average transfer RTG + average transfer ATG))

A score of 0 indicates ambiguity neutral behavior, a score between -1 and 0 shows ambiguity seeking behavior, and between 0 and 1 demonstrates ambiguity aversion. We used the same formula, this time based on transfers in the lottery, to extract an individual score of ambiguity preferences in the lottery.

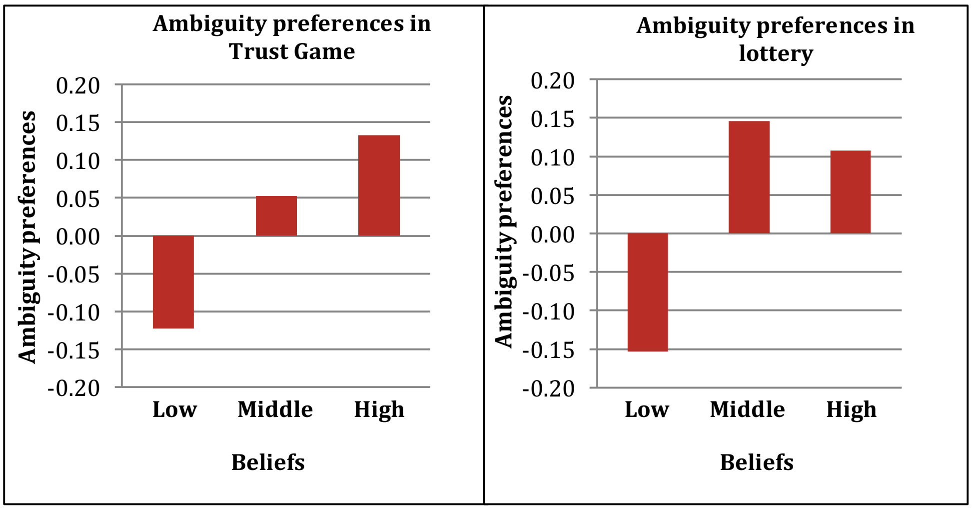
Ambiguity aversion in the social context increased as participants had higher beliefs regarding receivers' reciprocating behavior (ANOVA, $F(1,20) = 7.543$, $p=0.012$). Participants who thought two or three receivers would reciprocate scored lower on the normalized score for social ambiguity aversion than participants who thought 5 or 6 receivers would reciprocate (Figure 8a). In other words, the first group was ambiguity seeking, whereas the latter group expressed ambiguity aversion. In the lottery domain we also found that ambiguity aversion increased as the amount of winning colors increased. However, in the lottery context this relationship is less continuous as compared to the linear pattern observed in the social condition (Figure 8b).

Overall these results show clear individual differences in ambiguity preferences when taking participants' beliefs into account.

Ambiguity preferences in the social and non-social context were positively correlated. A participant who was ambiguity averse (seeking) in the lottery was also ambiguity averse (seeking) in the social context. However, if we took individual beliefs into account, the relationship between individual beliefs and ambiguity attitudes across the social and non-social domains was significantly different (MANOVA, $F(2,19) = 3.735$, $p=0.043$). Again, this illustrated that when taking individual beliefs into account, sources of uncertainty matter.

Figure 8: Individual differences in ambiguity preferences

Figure 8a *Figure 8b*



Ambiguity aversion in the Trust Game increases, as individual beliefs about Trustees' reciprocity are higher. In the non-social context this relationship is less continuous than in the social domain. We label participants' beliefs low when they think 2 or 3 receivers will reciprocate (n=7). We label participants' beliefs medium when they express a belief of 4 receivers to reciprocate (n=7). Finally, we group participants' beliefs when they think 5 or 6 receivers will reciprocate and label these high (n=8). Only for illustration purposes do we plot these effects for three separate groups, which are near to equal in size. These effects also hold when analyzing beliefs as a continuous variable ($p < 0.05$).

Neuroimaging results

We performed several analyses to understand the neural mechanisms of DMUU. First we investigated the main contrasts between the type and source of uncertainty. Subsequently, we studied the neural mechanisms of individual ambiguity preferences.

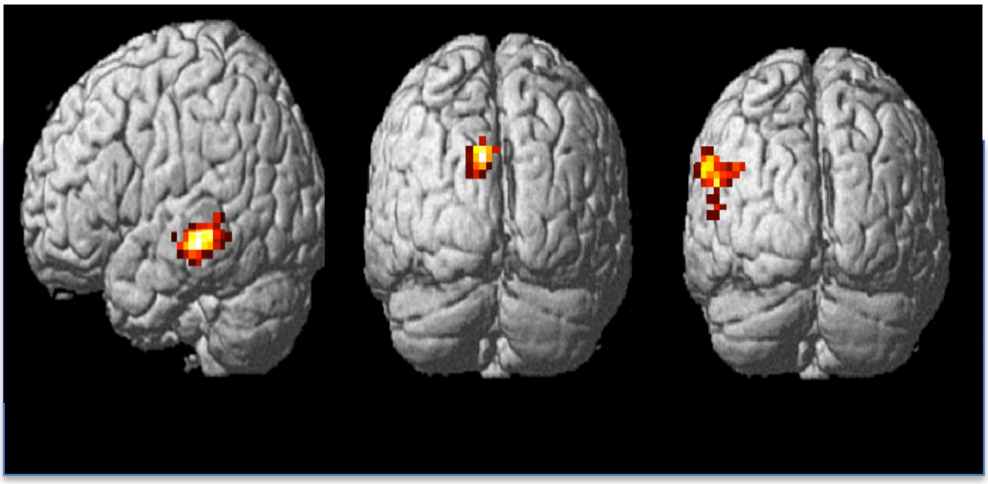
Main contrasts

The main contrast between ambiguity and risk, independent of the source of uncertainty, revealed bilateral activation in the middle temporal gyrus, the left inferior parietal lobule (both in angular and supramarginal gyrus) and the left superior parietal lobule (precuneus) (Figure 9 and Table 4). The main contrast between the social and non-social source of uncertainty yielded activation in the right and left fusiform gyrus and the right IFG.

Individual ambiguity preferences

Following up on our behavioral results, we added individual scores for social and lottery ambiguity preferences as covariates to the GLM model for the main contrast of ambiguity versus risk. We only found significant brain regions related to social ambiguity preferences. The greater ambiguity aversion in the social domain, the more activation was shown in the left (24 voxels) and right IFG (29 voxels) and the left inferior temporal gyrus (29 voxels) ($p < 0.001$, > 10 voxels).

Figure 9: Activity main condition ambiguity versus risk



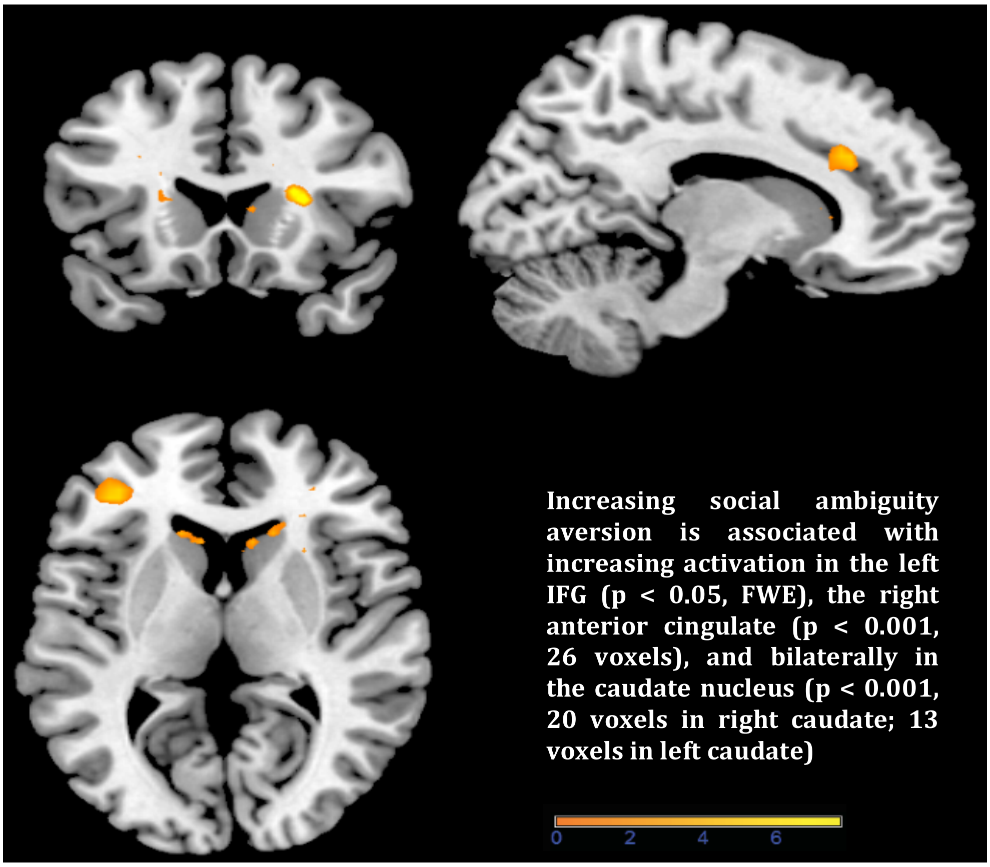
Significant clusters of activation when subjects make investment choices under ambiguity versus under risk: left middle temporal gyrus, left precuneus and left inferior parietal lobule (surpramarginal and angular gyrus). Not shown here, but also significantly active: right middle temporal gyrus.

Table 4: Overview brain regions

Brain regions	Hemisphere	Voxel number	Voxel t score	MNI coordinate of local maxima
Ambiguity > risk trials (main condition)				
Middle temporal gyrus	Left	142	6.1	-50,-32,-10; -36,-38,-4; -60,-28,-7
Middle temporal gyrus	Right	69	4.29	52,-24,-10; 48,-35,-7
Precuneus	Left	47	4.35	-8,-66,32; -12,-56,35
Supramarginal/Angular gyrus	Left	71	4.81	-57,-49,32; -46,-49,32 -54,-66,14
Risk > ambiguity trials (main condition)				
Fusiform gyrus, calcarine gyrus	Left	481	8.58	-29,-77,-14; -8,-94,-4; -29,-66,-18
Middle occipital gyrus; fusiform gyrus	Right	754	8.29	30,-66,32; 34,-70,-14; 38,-80,4
Social > non-social trials (main condition)				
Fusiform gyrus	Right	965	9.35	38,-46,-21; 27,-80,-10; 38,-80,7
Fusiform gyrus	Left	746	8.97	-36,-84,-7; -32,-56,-14; -36,-46,-14
Inferior frontal gyrus	Right	150	5.43	44,21,24; 52,10,28; 44,35,10
Ambiguity > risk: correlation with individual measure of social ambiguity preferences				
Inferior and middle temporal gyrus	Left	29	5.06	-50,-56,-14;-43,-63,-4
Inferior frontal gyrus	Right	29	4.58	55,14,24
Inferior frontal gyrus	Left	24	5.37	-46,32,21
Investment ambiguity > risky Trust Game: ANOVA on three different belief groups (contrast -1 0 1: increasing ambiguity aversion)				
Inferior and middle frontal gyrus	Left	45	4.96	-40,42,10; -36,42,18
Anterior Cingulate cortex	Right	26	4.88	13,28,28
Caudate nucleus	Right	20	4.27	16,24,7
Caudate nucleus	Left	13	4.35	-15,24,7; -18,21,10

In addition to looking at individual's aggregate score for ambiguity preferences, we also investigated investment choices on a trial-by-trial basis by adding investment amounts as parametric modulator to our GLM model. We first contrasted investment amounts in the ATG versus the RTG. Subsequently we performed an ANOVA on this contrast between three equal groups ranging from low to high beliefs in terms of their expectations concerning receivers' reciprocity (see Figure 8 for more details). An increase in ambiguity aversion over these three classes of participants yielded activation in the left IFG, the right anterior cingulate and bilaterally in the caudate nucleus (Figure 10).

Figure 10: Individual differences in brain activation related to social ambiguity preferences



Running the same ANOVA on the parametric contrast between the investment choices in the ALOT versus the RLOT did not reveal any significant brain activation.

Discussion

This study investigates DMUU by comparing social and non-social sources. Previous (fMRI) research has either focused on the dynamics of social interaction – playing against a computer versus a person – or the distinction between risk and ambiguity in lottery contexts. We examined a fourfold pattern of both the source and type of uncertainty. We believe this is crucial, as real life decisions are generally not determined by the flip of a coin or the roll of a die. People often face uncertainty that directly stems from the conscious choice of (an)other person(s).

It is challenging to study uncertain decision-making in a social context. Whereas underlying subjective probabilities can be easily manipulated in a lottery context, people have more idiosyncratic expectations in social environments, and it is essential to address these individual beliefs in order to have a useful comparison between different treatments. Our design took this into account by matching individual beliefs regarding the ambiguous social interaction to the other decision contexts, in order to ensure that any observed differences can be attributed to either the type or source of uncertainty, respectively. Taking these individual beliefs into account also allows us to explore individual differences in DMUU, demonstrating more than ambiguity aversion, typically the main focus of previous work on DMUU. This study also stresses the interaction between individual beliefs and individual differences in ambiguity preferences.

We find a significant behavioral main effect of ambiguity aversion. Participants invest less when the type of uncertainty is ambiguous as compared to when it is risky. This aversion is only observed in the social domain. The neural correlates of the main effect of ambiguity aversion reveal significant brain activity in the left and right middle temporal gyrus, left inferior parietal lobule (angular and surpramarginal gyrus) and left superior parietal lobule (precuneus). The implications of these neuroimaging results suggest that the underlying mechanisms of choice in ambiguous environments are somewhat context-independent as the brain regions that significantly correlate with ambiguity in our study do not differ from previous findings, which are on ambiguous lotteries (Bach et al., 2011; Huettel et al., 2005). Although the experimental set-up of Hsu et al. (2005) greatly differs from ours, they also find no differences in neural correlates of ambiguity preferences as measured via three different elicitation procedures: a lottery, a card-deck game and guessing the correct temperature in another city. This suggests that these areas are involved in a more general network of ambiguity processing, largely independent of the specific elicitation of uncertainty in this context, this providing a useful broader picture of how the brain deals with ambiguity.

In both social and non-social sources of ambiguity, we find that participants make use of their beliefs when making investment choices in the ATG and the provided number of winning colors in the ALOT. This expectation thus feeds into a subjective probability, which participants rely on in order to guide their DMUU. Risky decision-making already provides objective probability and participants do not need to establish an expectation that can serve as a subjective probability. As our neuroimaging results are similar to Bach et al. (2011) and Huettel et al. (2005) we also view ambiguity as more complex expected value calculation where one is integrating multiple possible subjective probability distributions.

Our second main finding is that ambiguity preferences are dependent on individual beliefs. When we take individual beliefs into account, ambiguity aversion is only part of the overall picture. In the social context, we find that ambiguity aversion increases as objective probabilities of reciprocation in the RTG increase. When individuals hold low beliefs concerning the reciprocity of others, participants invest more in the ATG than in belief-matched objective probability trials in the RTG. On the other hand, when individual beliefs regarding receivers' reciprocity are higher, participants invest less when they face social uncertainty in the ATG as compared to social risk in the RTG.

These results are consistent with the reverse S-shaped curve, a behavioral phenomenon well described in economics literature for lottery evoked choice events (Abdellaoui et al., 2011). This suggests a greater willingness to bet on risk than on ambiguity if the objective probability exceeds 0.5, and also suggests greater insensitivity to ambiguity than to risk. Likelihood insensitivity implies that people do not discriminate between changes in likelihood, but move towards the direction of a probability of 0.5. This pattern has previously only been observed in lottery contexts, whereas here we additionally identify this behavioral pattern in the social domain where the uncertainty stems from a human-made choice.

Behavioral studies that have looked into the effect of the reverse S-shaped curve elicit different data points, per individual, along the probability distribution. In our experiment we have participants that vary substantially in their social expectations and therefore these individuals naturally fall in clusters along the probability distribution. A participant who has pessimistic beliefs concerning the reciprocity of others is ambiguity seeking. A participant with optimistic beliefs concerning the reciprocity of others is much more ambiguity averse. But we cannot state anything about the ambiguity preferences of these individuals if they would have had other beliefs, or if we would have given different amount of winning colors in the ALOT (not matching their beliefs from the ATG). Nevertheless our findings relating to the interplay between social beliefs and ambiguity preferences is interesting and has important implications, but has to be put in the perspective of our experimental design.

Individual differences are also reflected in our neuroimaging results where significant clusters of brain activity relate to individual social ambiguity preferences, but not to lottery ambiguity preferences. Specifically, the IFG consistently correlates with individual social ambiguity preferences: this brain activation is found when adding individual's social ambiguity preferences as a covariate at the second level, and is also evident when modeling ambiguity aversion on a trial-by-trial basis as a parametric modulator.

Interestingly, Bach et al. (2011) also showed that right IFG activation correlated with individual differences in ambiguity preferences, in this case in a lottery context, as distinct from our findings indicating that the IFG specifically relates to social ambiguity preferences. However, on careful examination the Bach et al. (2011) lottery setup was framed in a rather 'social' manner. Participants were told that this lottery would be resolved via a game between two bowlers. Each bowler had a different colored ball, and the color of the ball indicated a first-order objective probability to win the lottery. Only one of the two bowlers would play, and depending on where the ball would land, participants could indicate which bowler had played. Participants therefore needed to integrate the position of the ball on the screen (second-order probabilities) with conditional first-order probabilities (which bowler had played). In this manner the study by Bach et al. (2011) addressed the question if second order uncertainty is different from the categorical difference between ambiguity and risk.

In our study individual differences in social ambiguity preferences were linked to the IFG. These findings are supported by results indicating that the IFG is involved with social cognition (Oberman et al., 2007). Single cell recording in macaques' premotor cortex demonstrated the existence of a unique set of premotor neurons, which responded when the monkey observed an action of somebody else and performing the action itself as well (Rizzolatti et al., 2001). In the human brain, the existence of a similar system has been found in the IFG (Fadiga et al., 1995), and use of repetitive transcranial magnetic stimulation (rTMS)[24] demonstrated a causal relationship between the left IFG and its necessity to make accurate perceptual judgments about other people's actions (Pobric et al., 2006). These findings can explain the role of the IFG in the study by Bach et al. (2011), whereby participants were thinking about the actions of the bowlers, which end position of the ball should be used for optimal DMUU. Also, the IFG, together with the inferior parietal lobule and the superior temporal sulcus, has been implicated in a network that tries to match perceptions of the environment with internal representations in order to act and decide appropriately (Parsons et al., 1995; Buccino et al., 2001; Iacoboni et al., 2001). Gallese et al. (2004) speculate that the IFG further developed in humans as to represent the underlying intentions and feelings of other people beyond the physical aspect of an action. In our study participants use their beliefs about the behavior of receivers to decide under uncertainty, without any need to observe or imitate

[24] rTMS is a non-invasive procedure whereby a pulsed magnetic field stimulates electrical activity in the brain, which subsequently excites or inhibits a certain brain area. Via rTMS a causal link between brain regions and behavior can be demonstrated.

actions. Overall, therefore, the IFG seems to be involved when players are making uncertain choices, but specifically when the uncertainty is resolved by a conscious move (as in Bach et al., 2011) or conscious decision of another person, which extends our knowledge about decisions made under uncertainty via the actions of another person.

Overall, this study demonstrates the unique feature of combining insights from economics and neuroscience in order to understand DMUU. The conceptualization and understanding of our behavioral results stem from economic theories. Neuroimaging data, on the other hand, increase our understanding of the mechanisms of making choices under uncertainty. Our fMRI results suggest that people use the same approach to tackle uncertain choices, irrespective of the particular decision domain: people form expectations and use these to guide their choices (Chang et al., 2011). Based on these beliefs, we can elucidate individual differences in ambiguity preferences, and the neural basis for these individual differences points to the role of the IFG in trying to assess the intentions of other humans in order to make decisions under social uncertainty.

This study is the first to simultaneously explore risk and ambiguity preferences in a social domain, with previous studies mostly relying on lotteries to elicit ambiguity preferences. Therefore, we are able to take a broader approach to this topic, as many, if not most, uncertainties we face in real life are related to the behavior of other people. Subsequently, previous studies have emphasized the role of ambiguity aversion on choice. The current study shows that individual beliefs vary in social interactive situations, and this has a direct effect on ambiguity preferences. Assessing choices in more real-life scenarios enables us to think about practical implications of our findings. For instance, our results suggest that people's reactions towards, for example, new policy measures are dependent on their expectations. Imagine a new policy measure, which is still somewhat unclear in how it might resolve in the future. A citizen with high expectations concerning the successful rollout of this policy measure greatly benefits from receiving more information, that is, when uncertainty becomes more risky than ambiguous. A citizen with low expectations on the other hand, would be more negatively affected when receiving pessimistic information corresponding to their set of beliefs. Future studies could usefully follow up on the unique interplay of individuals' beliefs within the framework of both the type and source of uncertainty.

Chapter 4

Anticipating rewards[25]

The power of beliefs in activating an expected reward signal in the ventral striatum

Introduction

Decision-making under conditions of uncertainty, that is, when we cannot exactly know the outcome of our choices, is often guided by the beliefs we have about the world. For example, we bring an umbrella to work based on our estimations of likelihood of rain later that day, and we choose to loan money to an acquaintance by assessing the chance our money will be repaid. The beliefs we generate about these situations, and how these beliefs are updated once we find out the outcome, are therefore critical in understanding this decision-making process. Economic theory assumes that decision-makers have beliefs about uncertain choice events (Savage, 1954), with these beliefs acting as subjective probabilities, which in turn guide individual choice under uncertainty (Wakker, 2010).[26] Beliefs can be instantiated in several ways, for instance based on specific knowledge, received information, and expertise in a particular domain (Fox and Tversky, 1995; Fox and Weber, 2002).

For example, imagine you are an investor who regularly reviews business plans and needs to decide which one to fund. Although you have experience in this domain, you also realize the world is uncertain, and therefore you carefully decide which project to fund based on your expectations about which entrepreneurs will successfully execute their business plan. You will learn if your expectations were correct when,

[25] This chapter is based on a joint paper with Alan Sanfey, Jana Vyrastekova and Utz Weitzel, Anticipating rewards. The power of beliefs in activating an expected reward signal in the ventral striatum, 2015, in preparation.
[26] Please see BOX 2 in the Introduction for more details on this model.

after several months, you receive the financial statements of the companies you funded. In particular you are interested in reviewing the projects you expected to do well and for which you anticipated a high return on investment.

Together, an investor's beliefs regarding successful execution of the business plan and the estimated return on investment feed into the expected reward from the decision. More broadly, decision-makers only ever get a full picture of the relationship between beliefs and decisions by examining the eventual outcomes of their decisions, which offers opportunity to learn whether the decision-maker's initial expectations are met, or were incorrectly assessed. Prior to learning the outcomes however, one can imagine, as might the investor, that anticipated rewards increase in correspondence to individual's beliefs, i.e. the higher the beliefs of obtaining a reward in the future, the higher the anticipated rewards themselves.

In this Chapter we are interested in the mediating role of beliefs for anticipating rewards. One typical task used to investigate anticipated rewards in humans is the monetary incentive delay task (MID; Knutson et al., 2000). Here, the decision-maker must respond via button press within a certain time-limit in order to receive a monetary reward. The essential feature of the MID is that before this reaction time task, players learn that certain visual cues that they will later respond to are associated with specific gains or losses, indicating either how large the monetary reward is, or how much they can avoid losing if they perform the button press task successfully. In the MID this cue-reward association is labeled anticipatory reward (Carter et al., 2009).

The MID paradigm used to elicit anticipatory rewards and punishments is based on earlier primate work (Knutson et al., 2001). Anticipatory reward in primates is studied using conditioning experiments in which arbitrary stimuli signal appetitive rewards. When these stimuli are repeatedly paired with an appetitive reward, these stimuli will change from unconditioned to conditioned stimuli (Schultz et al., 1997), with dopaminergic neurons modulating this process (Fiorillo et al., 2003; Schultz et al., 1998; Schultz, 2010). Dopamine firing will initially only occur when primates receive the appetitive reward itself, but once primates have learned the associations between stimuli and rewards, dopamine firing will then, and indeed only, respond when the conditioned stimuli appear (Schultz, 2010). Only in the event of the delivery of the appetitive reward unexpectedly changing following a conditioned stimuli will dopaminergic neuronal activity be observed at the time of reward delivery (Schultz, 2010).

In humans, the dopaminergic effects of rewards have been associated with activation in the ventral striatum, in particular the nucleus accumbens (NAcc), with this region's axons receiving dopaminergic input from the ventral tegmental area (VTA) in the midbrain (Schultz, 1998). Striatal activity has been observed for anticipatory rewards in a wide variety of modalities. For example, activation in the ventral striatum, mediated by abstract cue-associations, has been observed for monetary rewards (Knutson et al., 2001; Knutson and Greer, 2008), food (O'Doherty et al., 2002; Hare et al., 2008; 2009), social cooperation (Powers et al., 2013; Korn et al., 2012; Lin et al., 2012; Jones et al., 2011; Davey et al., 2009; Rilling et al., 2004) and even the punishment of others (Singer et al., 2006).

Though many studies have investigated the neural underpinnings of reward anticipation by varying the reward type and reward modality, to the best of our knowledge the method of evoking anticipatory rewards via abstract cues has never been adapted. Here, we investigate whether decision-makers' beliefs about the outcomes of their choices can also act as a cue for reward anticipation, that is, when the reward cue is a function of prior internal evaluations as opposed to an externally-provided association. In a similar vein as to how reward anticipatory mechanisms operate when a previously-learned cue is presented, we expect that people anticipate rewards when awaiting outcomes of previous decisions that were mediated by internal beliefs. When the investor from our earlier example anticipates a higher return from certain business projects, we would predict that these expectations would lead to increased reward anticipation prior to learning how these projects materialized. Mechanistically, we hypothesize that this process is mediated by activation in the ventral striatum when participants anticipate the receipt of their rewards.

To examine this question experimentally, that is, the neural mechanisms of belief-mediated anticipatory rewards, the first step is to elicit beliefs that can in turn be related to participants' decision-making. Once we observe that participant's decisions are indeed guided by their beliefs, we can then investigate the associated BOLD response as participants await the respective outcomes. The task should also involve incentivized DMUU, as dopaminergic modulation is primarily observed when rewards are actually valuable in an uncertain environment (Schultz, 2010).

In our design we distinguish between both sources and types of uncertainty. The sources of uncertainty we use stem from either a lottery or from the choices of another person. Though experimental investigations of uncertainty often employ a mechanistic flip of a coin or the roll of a die, people frequently face strategic uncertainty that directly stems from the conscious choice of (an)other person(s) (Trautmann and Vieider, 2011). Though anticipated rewards in a social and non-social setting may both be processed in the striatum (Lin et al., 2012), by using participants' own belief sets it could well be that participants rely more on their beliefs in a social context (Chang et al., 2011). Therefore we are interested in investigating if non-social and social sources of uncertainty influence belief-mediated anticipatory rewards in different ways.

By types of uncertainty, we distinguish between risk and ambiguity, that is events, which are characterized by known objective probabilities respectively unknown probabilities, in which case decision-makers need to rely on their subjective probabilities (Trautmann and van de Kuilen, 2013). Most of our daily decisions are ambiguous, as the majority of events we encounter cannot be fully defined in terms of exact probability estimation (Wakker, 2011). That is, we cannot express our decisions as a fair coin toss or the roll of a die. The majority of the experiments that employ the MID exclusively focus on ambiguity as type of uncertainty, meaning that anticipatory cues, which signal gains and losses, materialize under complete uncertainty. Uncertainty gets resolved when the outcome associated with the cue either occurs or does not occur, i.e. probability is 1 or 0 (Knutson and Greer, 2008). A few studies focused on neural differences of anticipated rewards when cue-reward associations materialize with known probabilities (risk) versus unknown probabilities (ambiguity). These studies show a distinct pattern of brain activation between anticipatory rewards under risk versus ambiguity (Volz et al., 2002; Tobler et al., 2006). These findings are in line with primate studies, which show that dopaminergic modulation of rewards varies across probability distributions (Fiorillo et al., 2003). By employing different types of uncertainty we can study anticipated rewards that are related to beliefs and from objective probabilities.

Therefore, we utilize here an incentivized task in which we can manipulate both the type – risk and ambiguity – and the source – social and non-social – of uncertainty. An essential feature of our design is the elicitation of individuals' beliefs prior to decision-making itself. This enables us to directly examine the influence of beliefs on decisions, and in the subsequent anticipatory reward signals we can observe while people await the decision outcomes.

Once participants view these outcomes, they likely compare their obtained rewards with those they expected based on their beliefs. This process is often labeled counterfactual thinking (Camille et al., 2004) and describes the comparison between what was gained versus what *could* have been gained. Unlike the feeling of disappointment that is typically experienced after a loss, several studies (e.g. Coricelli et al. 2005; 2007; Loomes and Sugden, 1982) have shown that the additional emotion of regret is involved when people make this comparison between the outcome of a choice and an unrealized, better, foregone alternative. Furthermore, Coricelli et al. (2005; 2007) show that this experience of regret is correlated with activity in the orbitofrontal cortex (OFC), which is distinct from both activity in the striatum following rewarding outcomes, or from activity in the middle temporal gyrus and dorsal brainstem following mere disappointment. Additional evidence regarding a causal role for the OFC in experiencing regret stems from patients with lesions to this region. Compared to healthy controls, these patients do not experience anticipated regret, but rather make judgments solely on the basis of the current choice without making any comparison to previous outcomes (Camille et al., 2004).

Our paradigm additionally allows us to examine how outcomes that deviate from our expectations are processed, i.e. those decisions that then likely induce decision regret. Therefore, a second aim of this study is to investigate the neural mechanisms of the actual experience of outcomes following participants' decision-making.

The affective state of regret has to date only been studied for risky lotteries, by letting participants make a binomial choice between two risky lotteries (Coricelli et al. 2005; 2007, Camille et al., 2004). Our design allows us to investigate counterfactual thinking in a richer environment that varies types and sources of uncertainty. Hereby we can address if risk versus ambiguity, a lottery versus a social source of uncertainty and this interaction affects the actual experience of obtaining a reward.

Taken together, our study aims to test how internally constructed beliefs, as opposed to the learned cue-outcome associations used in the MID, affect the neural mechanisms of reward anticipation. Based on the findings that anticipated rewards, via abstract cues, are coded in the ventral striatum, we hypothesize that belief-mediated anticipatory rewards will likewise activate the ventral striatum. We explore this question using an incentivized decision-making task that distinguishes between types and sources of uncertainty. This paradigm also allows us to study counterfactual thinking when decision-makers learn the actual outcomes. We specifically investigate if the OFC tracks the difference between what they expected and what they actually obtained in our decision-making task under uncertainty.

Methods

Participants

A total of 26 participants (mean age = 22, 50% female) were recruited for this study via the online recruitment system SONA of the Donders Institute for Brain, Cognition and Behaviour. Students with a psychology or economics background were excluded due to concerns about, respectively, suspicions regarding the veracity of the actual social interaction and a prior detailed understanding of game theoretic behavior.

Four of the 26 participants were excluded. One participant did not believe the real human interaction and the incentive scheme, one made the same choice on all trials, and another chose extreme options, varying more than two standard deviations from mean responses. Finally, one participant was excluded due to technical issues with the

MRI scanner. Therefore, unless explicitly noted, analyses reported here are based on 22 participants (mean age = 22, 12 females and 10 males).

Design

The experiment consisted of two parts, a decision phase and an outcome phase, which were separated by a short break. Here, we focus on the outcome phase. We have discussed the decision-making phase in detail in Chapter 3 of this thesis, however we explain here this phase in order to clarify the outcome phase.

On each trial, participants received an endowment of 10 tokens. Participants could then decide to invest any amount of these tokens in either a human partner (social source) or a lottery (non-social source), with the investment amount then tripled by the experimenter. Additionally, there were two different types of uncertainty regarding the likelihood of their investment being repaid, that of risk and of ambiguity, for a total of four experimental conditions.

In the social condition, the fMRI participant, termed the sender, has their (tripled) investment transferred to another player, known as the receiver. The receiver can then decide to either keep all of this investment, or return half of it to the sender. If half is sent back, the sender is obviously better off than if they had not transferred money, but at the time of decision faces uncertainty as to whether the receiver will reciprocate his or her trust. This is effectively a standard Trust Game (Berg et al., 1995).

Receivers' choices were collected during a behavioral session prior to the fMRI experiment. Receivers simply made a binomial choice to either return or keep the investment should a positive investment be received from the sender. Receivers could not condition their choice on the different investment amounts the sender could potentially invest with the receiver. Thereby our fMRI participants, in their role as sender, only act upon beliefs regarding receivers' trustworthy behavior and their decisions are not confounded by other motives of investing, for example signaling or elicitation of positive reciprocity.

In the non-social condition, participants' outcomes are resolved via a lottery, specifically a marble drawn from an urn, with this marble being either a 'winning' or 'losing' color. Again, the fMRI participant decides on a transfer, receiving back either half of the tripled investment (if a winning colored marble is drawn), or alternatively losing their entire investment (if a losing colored marble is drawn). This is a typical Ellsberg lottery design (Ellsberg, 1961).[27]

In both social and non-social decision contexts, participants saw trials where they explicitly knew the probabilities of either a reciprocating partner or a winning color respectively (risk condition), or where these probabilities were unknown (ambiguity conditions). Participants made investment choices across these four settings, known as the ambiguous trust game (ATG), risky trust game (RTG), ambiguous lottery (ALOT) and risky lottery (RLOT). We are able to create risky and ambiguous trials by introducing a group principle to the general feature of the games discussed above. In the Trust Game we group nine decisions made by nine different receivers. One receiver is randomly drawn from the pool of nine receivers and matched to the participant's investment choice. In the lottery there are nine marbles in the urn. One randomly drawn marble from this urn determines if the participant gets back half of his tripled investment.

In the social context participants have prior beliefs about the reciprocal behavior of receivers. Therefore we elicited individuals' beliefs in the ATG before participants made decisions in our experiment in the scanner. We asked how many receivers out of the pool of 9 they thought would reciprocate their investment. This belief is then used to offer participants *belief-corresponding* scenarios in the other experimental settings. Essentially, individual beliefs determined a tailor-made trial structure for each participant. For example if a participant expressed a belief that 3 out of 9 receivers would reciprocate in the ATG, this participant was informed during instructions that 3 out of 9 colors are winning colors in the ALOT. As the ALOT is an urn filled with nine marbles in an unknown color composition, receiving information regarding the number of winning colors is not similar to an objective probability in the RLOT. In the RTG, participants would most often make investment choices according to the belief-corresponding scenario, in this case three receivers out of

[27] Please see BOX 1 in the Introduction for an explanation of the experiment established by Daniel Ellsberg (1961).

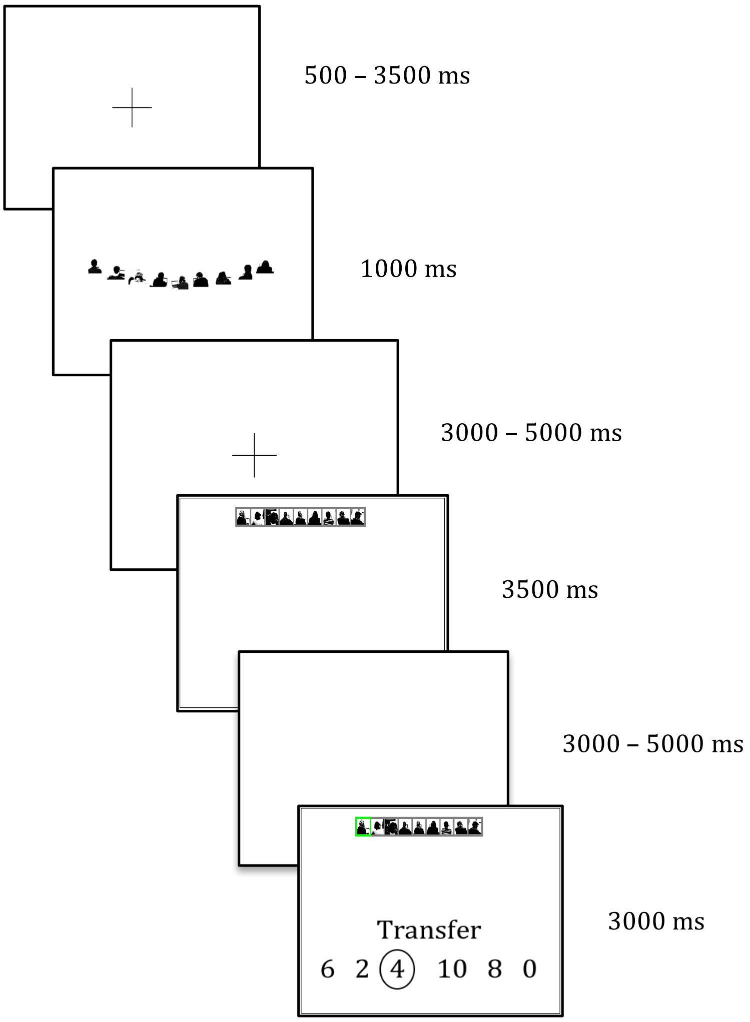
nine receivers will reciprocate. Lastly, a belief-corresponding scenario in the RLOT entails that three out of nine marbles are colored by a winning color (See Figure 5 in Chapter 3).

By implementing this feature we make sure that beliefs are aligned in our four settings. This enables us to investigate expected reward signals by examining the effect of both source and type of uncertainty, taking into account participant's beliefs. To reiterate, we focus here solely on the outcome phase, that is, after all decisions have been made (see Figure 11).

Two screens are of note. Firstly, we examine screen 4, which we term the *anticipation screen*; here participants are shown a choice setup and subsequent investment they themselves chose in the earlier decision phase. Then, they see the actual outcome of that trial, when a randomly selected receiver (social condition) or marble (nonsocial condition) is selected (final screen Figure 11, henceforth referred to as the *outcome screen)*. When the selected receiver or marble is highlighted green this indicates a winning trial, and when colored red indicates a losing trial. After each block of six trials from both the social and non-social condition, one trial from both contexts was randomly selected for actual payment (Figure 12). After the experiment tokens were converted to Euros and participants were paid accordingly.

The fMRI task was presented using Psychtoolbox (Matlab). Participants read instructions and performed a belief elicitation task (75 minutes in total) before they were placed in the MRI scanner for approximately 60 min. They saw a total of 96 trials in the scanner, equally divided between outcomes in the Trust Game and the lottery. The outcomes were presented in 16 blocks, with each block consisting of six trials of either Trust Game or lottery outcomes. Within each block both risky and ambiguous trials were presented in a random order. As outlined above, the exact set of risky trials was tailored to each participant's belief regarding receivers' return choice in the ATG. In addition, we also had filler trials for other probabilities that did not match participants' beliefs. These trials were not included in the fMRI analyses. After the experiment subjects were paid out in cash dependent on their choices and randomly selected outcomes. Please see the Appendix for the instructions and the payment scheme.

Figure 11: Illustration of an outcome trial

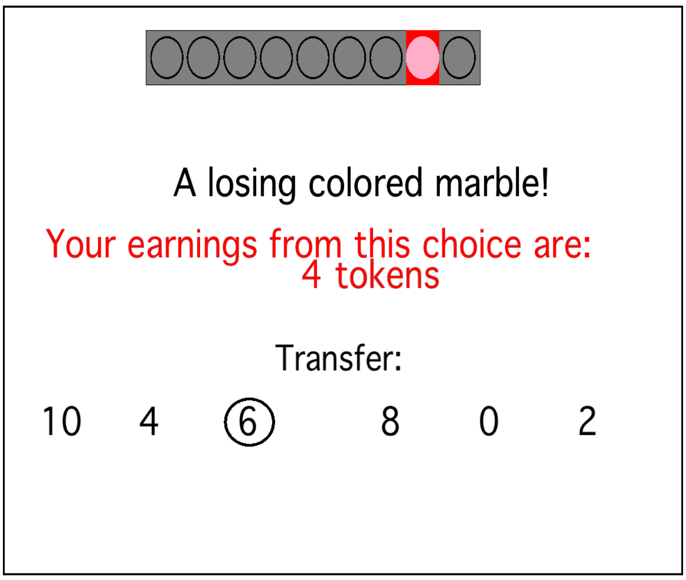


Above you can see an outcome related to ATG. We took pictures of receivers while they were seated behind a laptop. The pictures only show receivers' silhouettes in black and white and no facial features are shown.

Image acquisition

Functional neuroimaging data was collected on a 3-Tesla Siemens MRI system (Skyra) at the Donders Centre for Cognitive Neuroimaging in Nijmegen, The Netherlands. Images were acquired using a 32-channel head coil, with a standard multi-echo imaging pulse T2*-weighted sequence (field of view = 224 mm, matrix = 64 × 64, repetition time (TR) = 2390 ms; echo times (TE) = 9.4 ms, 20.6 ms, 32.0 ms, 43.0 ms, 54.0 ms, flip angle = 90°, slice gap = 0.5 mm). Using a multi-echo sequence provides a better signal-to-noise ratio for brain areas susceptible to dropout, while allowing for scanning of the whole brain (Poser et al., 2006). One whole-brain volume consisted of thirty-one ascending slices (slice thickness = 3.0 mm, voxel size = 3.5 × 3.5 × 3.0 mm). For each participant we acquired a high-resolution anatomical T1-weighted image (MPRAGE; 192 slices; TR = 2300 ms, voxel size = 1 × 1 × 1 mm). Participants' heads were loosely taped to the coil within the scanner in order to limit movement during image acquisition.

Figure 12: A randomly selected choice from the ALOT informing participants how many tokens they won.



Data analyses

Behavioral parameters

During the outcome phase no actual decision-making takes place. We do use two parameters from the previous decision-making phase that are relevant when participants view the associated outcomes.

The first parameter is the previously made investment choices, which participants passively review while anticipating either a gain or a loss.

The second parameter of interest is the optimal amount of investment in the case of a gain (when the participant is matched with a TG receiver who reciprocated or a winning colored marble in the lottery) or a loss (the participant is matched with a non-reciprocating receiver in the TG or a losing colored marble in the lottery).[28] When a participant faces a gain, irrespective of the specific source of uncertainty, she should have invested all her 10 tokens. Any deviation from an investment of 10 tokens is what we label as regret: you won, but you could have won more when invested more tokens. To be precise, this variable subtracts the participant's investment from the optimal amount invested, which is 10 tokens, in case she faces a gain. The higher this variable, themore tokens she has foregone, and the more regret she arguably feels. This variable is created for both the lottery and TG setting. On the other hand, when a participant loses, she will lose most when she invested all her tokens. Any positive deviation from 0 token will increase the amount lost and we label this as rejoice. To be precise, here we take the participant's investment amount, in case she faces a loss. The higher this variable, the more tokens she loses, and the more rejoice she arguably feels. Again, this variable is created for both the lottery and TG setting. Together we have four variables: regret in the lottery, regret in the TG, rejoice in the lottery and rejoice in the TG.

[28] We collapsed the risky and ambiguous trials due to the restricted number of trials in which participants either faced a gain or a loss in each of our four conditions.

Neuroimaging analyses

To study the neural mechanisms of reward anticipation, we examined the BOLD response during trials in which participants review their previously made choices and await their outcome (fourth screen Figure 11). The main regressors for these relevant trials indicate the onsets of the anticipation screens when participants either played the RTG (belief-corresponding risky trials), ATG, RLOT (belief-corresponding risky trials), and ALOT. We refer to this model as the *anticipation model*. To test if participant's investment behavior serves as a cue that triggers expected rewards, we add this variable as parametric modulator to the anticipation model.

To study the underlying neural mechanisms of the outcomes themselves, we analyzed the BOLD response of trials in which participants experience gains and losses (sixth screen Figure 1). Our main regressors for these relevant trials are the onsets of all outcome screens of the RTG (belief-corresponding risky trials), ATG, RLOT (belief-corresponding risky trials), and ALOT. We refer to this model as the *outcome model*. To study the effect of regret and rejoice we add these variables as parametric modulators, respectively attached to the onsets of gain trials and loss trials.

The regressors were modeled with a canonical hemodynamic response function during a time-window of two seconds after the onset of the screen. To account for residual variance, we also included the temporal derivatives of each regressor. Then, the motion parameters from realignment, including its quadratic effect and first derivative (in total 18 motion parameters per individual), were included in the generalized linear model (GLM). A standard high-pass filter (cut-off 128 seconds) was used during the GLM analysis to account for possible slow-frequency drifts. Finally, a whole-brain second-level model was used to analyze group effects for the specified contrasts discussed in the results section. Individual beliefs were always included as a covariate. Statistical maps were corrected for multiple comparisons using whole-brain cluster correction with an initial threshold of $p < 0.001$ and a Family Wise Error corrected cluster threshold of $p < 0.05$. Some contrasts also mention clusters, at $p < 0.001$ uncorrected (> 30 voxels).

Results

Beliefs and decision-making under uncertainty

In the ATG, participants decided how much to invest with a receiver without knowledge of the exact likelihood of reciprocation across receivers. Figure 13a shows a positive correlation between participants' beliefs, elicited prior to decision-making outside the scanner, and investment behavior in the ATG (r=0.642, p=0.001). The greater number of receivers that our fMRI participants thought would be present in a group of 9 receivers, the more tokens they invested.

Figure 13b shows that participants invested more in the ALOT as they saw more winning colors from the set of nine potential colors (r=0.597, p=0.003). As expected, in both social and non-social contexts, the higher the probability of receiving half of the tripled investment back, the more tokens participants invested.

Figure 13 Beliefs and transfer in ATG and ALOT

Figure 13a

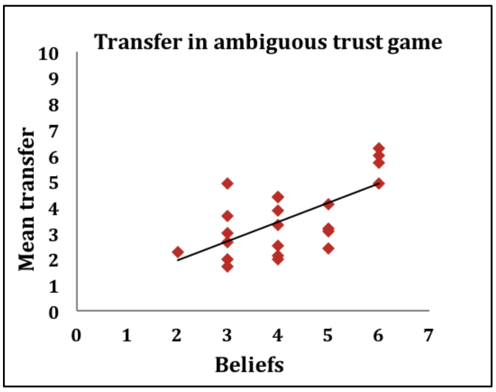
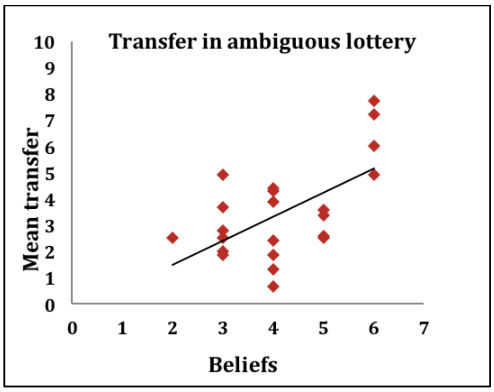


Figure 13b



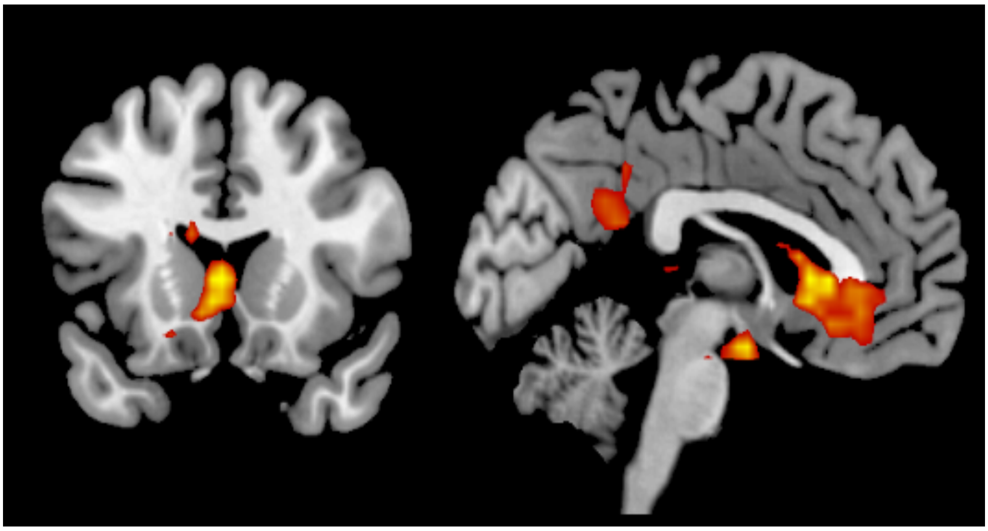
Elicited beliefs influenced chosen transfer in the ATG. Based on individual beliefs, participants received a matching amount of winning colors in the ALOT. Particpants included this information, given during instructions prior to the experiment in the MRI scanner, as transfer positively increased as afunction of the amount of winning colors.

Although these results may sound very intuitive, these are trivial for the upcoming neuroimaging analyses. Namely, when we add participant's investment choices to our fMRI models we can reliably state that these investments are guided by their individual beliefs.

Imaging data

We first focused on our primary research question concerning the anticipation phase. Did participants who invested most, which as we showed earlier is influenced by their beliefs about reciprocity, show a greater expected reward signal while they reviewed their chosen investment prior to seeing the outcome (fourth screen in Figure 11)? We indeed found that the more one invested in the Trust Game, as compared to the lottery context, the more activation was observed in an area that encompassed both the left ventral caudate and NAcc (Figure 14). Although this activation appeared to extend into the lateral ventricle, we lowered the statistical threshold to verify that the activation stemmed from the striatum.

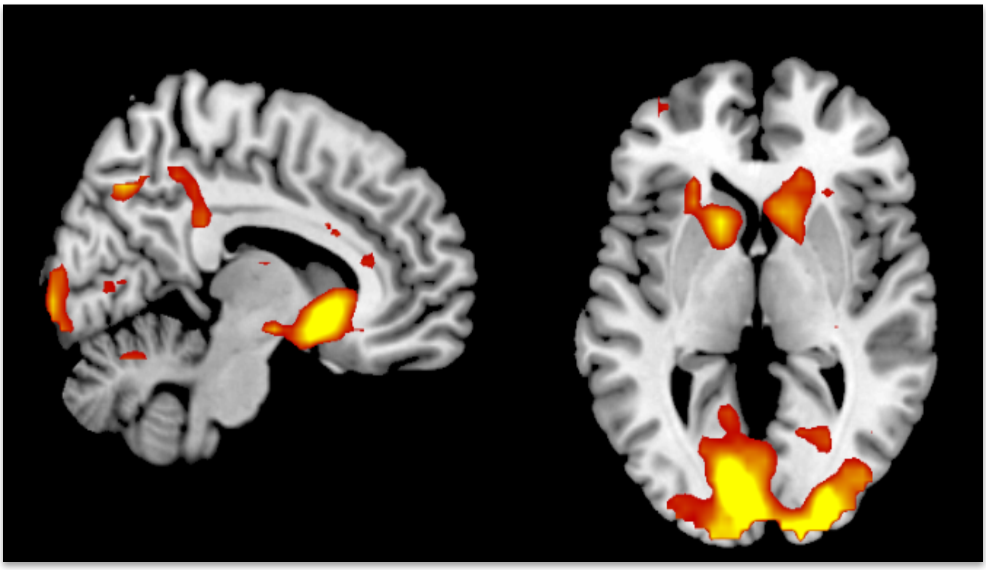
Figure 14: Anticipating rewards in the social context activates left ventral striatum (FWE < 0.05).



Although sources of uncertainty influence belief-mediated rewards, as shown above, we could not identify neural differences for types of uncertainty, i.e. we did not find differences in brain activation between anticipated rewards, which stem for risky trials versus ambiguous trials.

Then, we examined the question of neural differences when outcomes resolved (outcome screens) Firstly, to replicate previous findings, we investigated the contrast between experiencing a gain versus a loss during the outcome phase, collapsed across experimental conditions (last screen in Figure 11), which exhibited strong bilateral activation in the striatum (dorsal caudate) (FWE p<0.05) (Figure 15). The reverse contrast, a loss versus a gain, did not yield any striatal activation, even at a lowered threshold.

Figure 15: Bilateral activation in the striatum as participants experience a gain over a loss when reviewing their outcomes (FWE < 0.05).

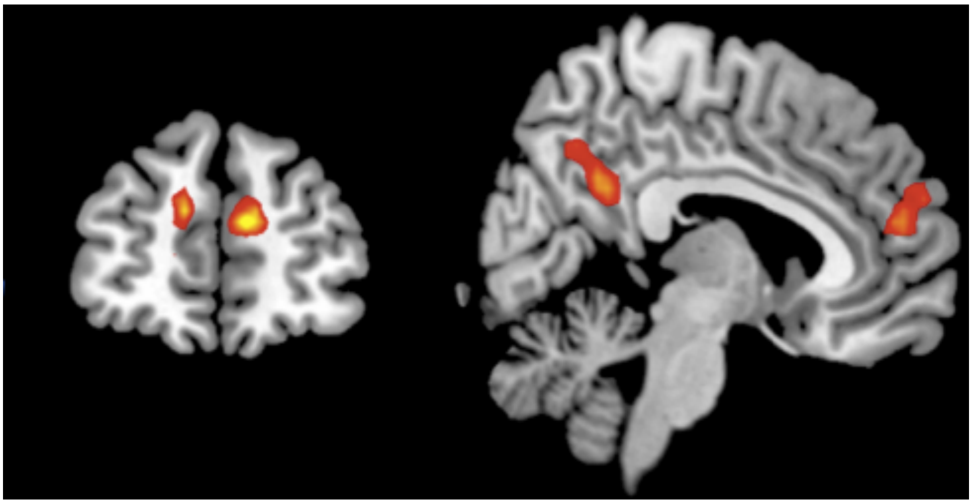


From the monkey research it was shown that, initially, dopamine neurons respond to rewards, but once cue-outcome associations are learnt, dopamine neurons will not fire at the time the rewards gets delivered. Only in case the reward unexpectedly changed, would dopaminergic neuronal activity be observed (Schultz, 2010). In our setup, this would imply that receiving a back-transfer would not come as much as a surprise for participants with high beliefs. Yet, participants who had low beliefs would presumably not expect a gain, and when one would experience a gain, it would therefore be somewhat surprising. We divided our participants in three equal groups, namely those with low beliefs (who think only two or three receivers will reciprocate), those with medium beliefs (think that 4 will reciprocate), and those with high beliefs (think that five or six will reciprocate).[29] We performed an ANOVA between these three groups on the contrast gain vs. loss collapsed across all conditions. We indeed found greater striatal activation when the outcomes were resolved for these participants who had the lowest beliefs regarding the likelihood of their investment being returned by a receiver or the draw of a marble with a winning color in the lottery.

As we had only found effects of sources of uncertainty on belief-mediated rewards, we also specifically investigated BOLD during the outcome screen (collapsed across conditions of risk and ambiguity and across gain/loss) when participants viewed their selected receiver in the social context as compared to their selected marble in the lottery. This contrast exhibiting increased activation for the social context in the dmPFC and precuneus (Figure 16).

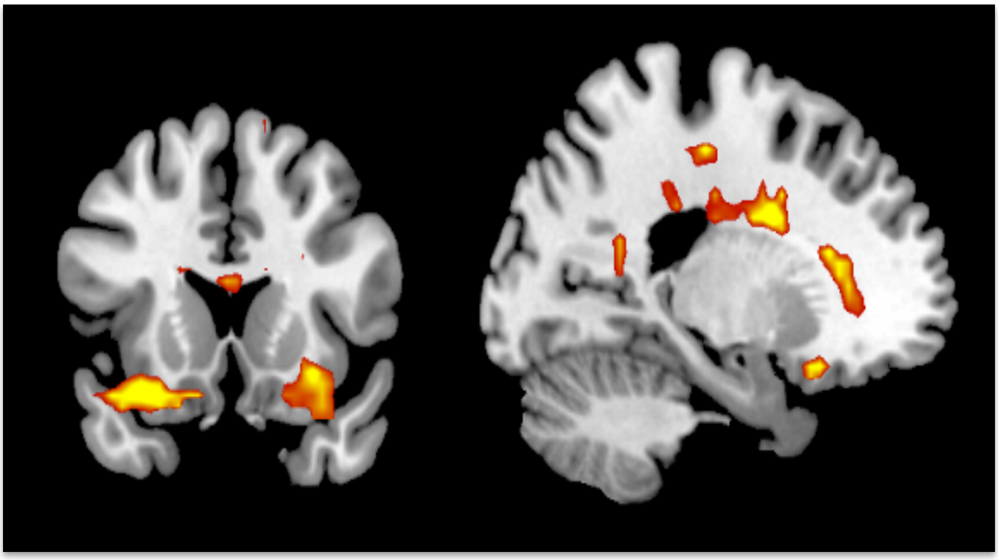
[29] Based on their beliefs, our fMRI participants naturally fell in these three groups of (near to) equal sizes (see Chapter 3 for the exact numbers). As we had shown in the previous Chapter that ambiguity preferences were greatly influenced by individual beliefs, by treating beliefs as a continuous variable and as a categorical variable of three groups of participants, we also wanted to look at the neural effect of beliefs when outcomes are resolved. As the relationship between beliefs and ambiguity preferences in the lottery showed a more non-linear relationship (see Figure 4b in Chapter 3), we chose to answer this question here with an ANOVA by categorizing participants in three equal groups based on their beliefs.

Figure 16: While participants experience their outcomes in the social versus lottery conditions, neural activation in the the mPFC and precuneus is found (FWE < 0.05).



Finally, we analyzed the BOLD response when participants viewed their outcomes in light of the interaction between experiencing a gain or a loss and the corresponding optimal investment they should have chosen to maximize rewards or minimize losses. To do this, we added the variables that coded for regret and rejoice as parametric modulators to our GLM model for the outcome screen. Whereas no correlation between BOLD and regret was detected, a baseline effect of rejoice (the effect of rejoice compared to all other regressors in the outcome model being set to zero) bilaterally activated the IFG and the supplementary motor area. Only in the lottery context did the contrast of rejoice versus regret show activation in the left insula extending to the orbitofrontal pole ($p<0.001$ uncorrected, 34 voxels) and in the right IFG (FWE $p<0.05$) (Figure 17).

Figure 17: Negative regret in the lottery context activates the left insula and orbitofrontal pole (p < 0.001 uncorrected, > 30 voxels)



Discussion

Reward anticipation is a well-studied topic in the field of Neuroeconomics (Knutson et al., 2008). In the wake of innovative primate studies, a growing literature has emerged examining the putative dopaminergic modulation of rewards (Schultz et al., 1997; Schultz et al., 1998), with the MID being a typical task used to study the neural underpinnings of reward anticipation in humans (Knutson et al., 2000). Our study sought to implement a procedure in which anticipated rewards stem from individuals' beliefs and their subsequent decision-making under uncertainty instead of learned cue-outcome associations that is typically evident in tasks such as the MID. In this experiment, we examined the power of individuals' beliefs when making decisions under uncertainty. We aimed to show that these belief-mediated anticipated rewards are processed in our brain as an expected reward signal, similarly if these rewards are evoked through abstract cue-outcome associations.

Choices made by participants in both the Trust Game and the lottery tasks indicate clearly that underlying beliefs guide participants' DMUU. Participants invest more when they expect more of their game partners to reciprocate their investment in the ATG. Similarly, in the ALOT participants invest most when they know a greater number of colors out of the nine possible colors will lead to a return on their investment.

Our neuroimaging analyses then focused on whether these belief-related expectation signals were evident in brain regions related to standard cue-based reward anticipation. We found confirmatory evidence of this, with the greater the expectation of receiving a back-transfer in the Trust Game, the greater the investment amount, and in turn the higher the activation in a region encompassing the left ventral caudate and NAcc. Many previous studies have established that these regions track expected reward when cues with explicit reward and punishment values are shown to participants (Knutson and Greer, 2008). Our novel result illustrates that one's own investment choice, modulated by expectations regarding receivers' reciprocating behavior, serves as a similar type of anticipatory cue. This cue is not externally provided nor learned in a Pavlovian manner such as in an MID task, but rather is internally constructed via participants' own beliefs about the world. This finding illustrates that eliciting participants' own beliefs is just as powerful in evoking anticipated rewards as going through the effort of letting participants learn to associate abstract cues with gains and losses.

Interestingly, we did not find a similar anticipated reward signal in our lottery contexts. Participants were also provided with a belief-corresponding scenario in the ALOT, with the number of winning colors matching their belief in the ATG, as we did not want to confound the underlying source of uncertainty by different sets of beliefs. One consequence of this approach is that participants in the ALOT did not actively have to form a prior belief. A feature of dopaminergic modulation of reward is that the more uncertain a reward is, the more information the consequent outcome will reveal to enable an updating of priors. Although a different ambiguous urn was constructed on every trial in the ALOT, participants knew how many colors were winning colors. Firstly, this feature might have reduced the uncertainty as compared to the ATG, and secondly, beliefs may be simply weaker cues in the ALOT as compared to the ATG, perhaps due to increased engagement when dealing with other people as opposed to mechanistic devices. This latter explanation is corroborated by the findings that the dmPFC and precuneus were active when participants viewed their selected receiver in the social context, as compared to their selected marble in the lottery. These areas have been linked to theory of mind (De Martino et al., 2013; Frith and Frith, 2006; Hampton et al., 2008). These fMRI results suggest that participants consider the intentions of their matched partners during outcome trials.

Our design also allowed the possibility to look more specifically at the neural effects when participants experience outcomes that matched or are at odds with their expectations. Namely, when participants experience a gain or a loss, they should have invested all respectively zero tokens to maximize gains or minimize losses. Sources and types of uncertainty induced in our experiment might lead participants not to follow this optimal behavior The contrast of rejoice versus regret activates the left insula and orbitofrontal pole when the source of uncertainty stems from a lottery, which is consistent with data (Coricelli et al. 2005, 2007) regarding the neural underpinnings of counterfactual thinking in lotteries.

The effect of rejoice was only observed in the lottery context. Camille et al. (2004) argue that regret arises due to personal responsibility for the consequence of one's own choice. A potential suggestion is that one feels more responsible for the loss in the lottery context, as one cannot easily argue that this loss is due to the conscious action by somebody else like in the Trust Game. While in the social context one could more easily blame somebody else for not returning an investment, it is more difficult to attribute negative intentions to a random mechanistic device, which draws a losing colored marble.

Within the field of Economics it is common practice to elicit beliefs and use these as independent variables for DMUU. Neuroimaging studies on reward processing have typically neglected the role of beliefs, but rather have generally used externally provided cues to examine DMUU. Based on our results in this Chapter, as well as the results from the previous Chapter, we stress the influence of individual beliefs on DMUU and belief-mediated anticipated rewards.

When neuroimaging studies leave out individual beliefs, they will miss an important aspect of decision-making, and subsequently they will miss an opportunity to discover individual variance in decision-making. Yet, Neuroscience addresses questions not considered in Economics (Etner et al., 2012), for example how beliefs come about, how they are shaped, and to what extent are they adaptive (Vilares and Kording, 2011). Therefore one potential follow-up of this study is to design a dynamic experiment in which participants would be able to change future decision-making as a function of individuals' beliefs, which arguably will get updated as participants learn their outcomes. Nonetheless, this Chapter stresses the power of belief-mediated anticipated rewards as we can show an expected reward signal in the absence of live decision-making. Likewise, very recent studies were able to infer the choices people would make (if given the opportunity) based on their neural responses to simply viewing specific prospects without actual decision-making (Smith et al., 2013; Tusche et al., 2010; Levy et al., 2011). Altogether, by combining the instrumental use of cues in anticipating rewards with the role of beliefs in DMUU, this Chapter shows how Neuroeconomics can contribute to an existing rich literature on neural mechanisms of anticipated rewards.

Chapter 5

Ambiguity attitudes and borrowing behavior[30]

Introduction

Since the publication of the well-known Ellsberg paradox (1961), ambiguity aversion has been found and replicated in many laboratory studies (Trautmann and van de Kuilen, 2013)[31]. This aversion entails a preference for risky over ambiguous prospects that are equivalent under SEU. Ambiguity aversion is not a universal behavioral trait, but domain specific. Likelihood insensitivity under ambiguity, for instance, describes the phenomenon that most people are ambiguity averse for high likelihood events, while ambiguity seeking for low likelihood events. This behavioral pattern, which is sometimes referred to as a-insensitivity (henceforth simply insensitivity), indicates that a person does not sufficiently discriminate between various likelihoods (Wakker, 2010). With the term 'ambiguity attitude' we refer to both ambiguity aversion and insensitivity.

Although there is a substantial body of literature that has studied ambiguity attitudes in a variety of experimental contexts in the laboratory (Trautmann and van de Kuilen, 2013), only few studies investigated the external validity of experimentally elicited ambiguity attitudes by linking them to real life decision-making. For ambiguity aversion, Sutter et al. (2013) report a negative association with smoking behavior in adolescents. Dimmock et al. (2015a) show that ambiguity aversion positively affects retirement planning. In the field of developmental economics, Engle-Warnick et al. (2007) find negative

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[30] This chapter is based on a joint paper with Utz Weitzel, Ambiguity attitudes and borrowing behavior, 2015, under review.

[31] Please see BOX 1 of the Introduction for an explanation of the experiment by Daniel Ellsberg (1961).

effects of ambiguity aversion on the adoption of new varieties of crop in Peruvian farmers and Ross et al. (2012) report a negative relationship with the adoption of new variety of rice. For insensitivity, Dimmock et al. (2015a) report a negative relation with stock market participation and private business ownership, and a positive relationship with being insured (Dimmock et al., 2015b). This emerging literature shows that there is a need for more research that investigates whether specific behavioral patterns, as we observe them in the real world, are indeed driven by ambiguity attitudes that are measured in the lab (Trautmann and van de Kuilen, 2013).

We contribute to this literature by investigating the relationship between ambiguity attitudes and student borrowing behavior of 233 students in the Netherlands. This type of decision-making has not been related to experimentally elicited ambiguity attitudes before. This is surprising as student borrowing is an important policy instrument for the Dutch government (see next section) and elsewhere. Although a substantial share of students (35 percent) in the Netherlands take out student loans (Nibud, 2012), the majority prefers to finance their studies with a part-time job. Unfortunately, part-time jobs affect the total amount of time spent on studying. Due to the high number of students with a part-time job, the average study duration in The Netherlands is nearly six years, while most curriculums are designed for four yours only (Oosterbeek and van den Broek, 2009). This situation is not unique to the Netherlands as countries like the UK, the US and Australia face similar problems. In these countries, students face much higher education and admission fees compared to the Netherlands, which aggravates the problem for students who want to avoid loans (Institute for Higher Education Policy and Excelencia in Education, 2008).

A number of studies focus on debt aversion amongst students. Fear of debt and the prospect of accumulating debt can even influence the decision to study in the first place. This is especially prevalent among low socio-economic groups (Callender and Jackson, 2005; 2008). The majority of studies measure debt aversion and determinants for debt aversion with survey items like ‘owing money is basically wrong’, ‘there is no excuse for borrowing money’, or proxy questions like ‘do you usually pay off your credit card balances each month (conditional on having any)?'. The study of Eckel et al. (2007) is a notable exception. The authors experimentally elicit debt aversion as well as risk and time preferences with Canadian adults. The authors find "no evidence that debt aversion is an important barrier to investment in postsecondary education" (p.234). They do find, however, that risk-seeking and patient persons are more likely to take up education financing, supporting the notion that investing in education is a relatively risky choice.

We complement this literature by measuring ambiguity aversion and its relationship with student's borrowing behavior for education. We argue that taking out student loans is less about risk, where possible states and probabilities are perfectly known, but more about ambiguity, where probabilities for possible states are not known. In the latter case, students' aversion to borrowing may be primarily driven by their aversion to ambiguity regarding the repayment of their loans. Students are uncertain if they will be able to repay their debt after having obtained a degree, and also if they will graduate in the first place. Graduation and a decent job most likely ensure the ability to pay off debt in the future, but this goal is several years and numerous ambiguous events away. Yet students have to decide at the start of their study program whether to take out a student loan and, importantly, how much. The higher the stakes, the more confident a student needs to be that she will be able to repay the loan (Hill, 2013).

As explained in more detail in the next section, Dutch students face a multitude of ambiguous elements in the decision to take out a loan, including uncertain interest rates. Accordingly, we expect that students who are more ambiguity averse will borrow less than other students. Furthermore, we expect a negative relationship between insensitivity and borrowing. Insensitivity predicts that most people will overweight low likelihood ambiguous events of bad outcomes. In the context of this study such a low-likelihood event could be a complete loan default. We therefore predict that students who exhibit high insensitivity will overweight the likelihood of a loan default, and will try to either refrain from borrowing completely, or borrow as little as possible.

We elicit ambiguity aversion and insensitivity based on matching probabilities of three uncertain events with the following likelihoods: 0.1, 0.5 and 0.9 (Abdellaoui et al., 2011; Dimmock et al., 2015a; 2015b). After eliciting participants' ambiguity attitudes, students answer a variety of questions concerning their borrowing behavior. We find both ambiguity aversion and insensitivity in our sample. In line with much larger representative samples (Biermans et al., 2003; van den Broek and Van de Wiel, 2005; Oosterbeek and van den Broek, 2009), we find that 33 percent of our participants have a student loan. We cannot reject our null hypothesis that ambiguity attitudes and borrowing behavior are unrelated. Thus we do not find a relationship between ambiguity attitudes and the decision to take out a student loan. Subsequently, we find no relationship between insensitivity and student borrowing. A potential reason why insensitivity does not influence student borrowing may be that the likelihood of a loan default is not low enough that people would be insensitive to it or overweight its probability. In fact, in the Netherlands the default rate on student loans increased from 11 percent in 2009 to 15.63 percent in 2013 (Figures from Dutch Ministry of Education, 2014). Within the sub sample of borrowers we do find that ambiguity aversion is negatively related to the amount they borrow: the more ambiguity averse, the less a student borrows. These findings hold when controlling for the number of study years, gender, study background, risk preferences, income, financial literacy, scores on the cognitive reflection test and living situation

In the next section we will explain the system of issuing student loans in the Netherlands and its inherent ambiguity. Section 3 describes the experimental design and how we elicited ambiguity attitudes. Section 4 presents the results and section 5 concludes.

Student loans in The Netherlands

In the Netherlands, students can get two kinds of financial support from the government: a basic scholarship and a student loan. Most students receive a basic government scholarship. The exact amount depends on the individual's and family's wealth and income level. Students receive the basic scholarship for up to four years, because the majority of curriculums are set up as four-year programs (three years bachelor; one year master). Next to this scholarship, almost all students are able to take out student loans that are subsidized and issued by the government. Students can borrow up to €301,27 per month. After four years of study, when the basic scholarship ends, students can borrow up to €916,96 per month for three more years. As the student loans by the government have more favorable terms than individual bank loans, the latter are rarely used by Dutch students for secondary education (Nibud, 2012).

Practically every student is eligible for the full loan amount and application is very easy. All that a student needs to do is visit the webpage of DUO (the relevant governmental agency of the Dutch Ministry of Education) and enter the required information. The web site is very transparent and accessible and no additional mailings or requirements are needed. A student who decides to take out a student loan will receive the first loan payment within a month.

If a student graduates within ten years, the basic scholarship will be awarded as a gift. The student loan has to be repaid. The interest rate on government student loans are based on the current government interest rate and are therefore much lower than the interest rate a bank would issue on loans. While studying, students already incur interest costs based on the current interest rate. Two years after a student graduates, the repayment period starts and the graduate has to repay a fixed monthly amount. During the repayment period, interest costs on the remaining loan are still incurred. The graduate will be informed about this interest rate at the start of the repayment period. Every five years this interest rate is adjusted for a new period of five years. The repayment period has a maximum of 15 years, but graduates can choose to repay faster.

A student who decides to take out a student loan has information on the current interest rate, but she is uncertain about the different interest rates that will apply in the following years of study and during the various repayment periods. On its web page, DUO and the Ministry of Education offer calculation modules to estimate future loan repayments. The estimated monthly repayment amounts are provided for four different possible interest rates that could apply in the future. There is no information provided about the consequences when a student is unable to repay her loans.

A student, who decides to borrow now, can do so with a few mouse clicks. Yet she does not know the exact amount that she needs to repay in the future. She does not know the exact interest rate that will apply. She does not know what actions can be taken if she will be unable to repay in the future. Overall, there is substantial ambiguity about the consequences of the decision to take out a student loan at this moment in time.

Experimental design

Measuring ambiguity attitudes with matching probabilities

The method we used to elicit ambiguity attitudes is based on a simple and tractable method developed by Abdellaoui et al. (2011) and is known as probability matching. The idea is to elicit probability equivalents of a specific uncertain prospect that makes the subject indifferent between gambling on an uncertain and a risky prospect. One of the merits of matching probabilities is that ambiguity attitudes are directly measured relative to risk attitudes, thereby ruling out risk aversion or probability weighting as confounding factors. We estimated individual's ambiguity attitudes based on matched probabilities of three uncertain events with underlying likelihoods: 0.1, 0.5 and 0.9.

The unknown and the risky events in our experiment are operationalized via the standard Ellsberg urn setup (1961). The unknown urn was composed of 100 colored chips in an unknown composition. If the underlying likelihood of the unknown urn was 0.5 (henceforth U2), all chips in U2 were of one of two colors: yellow or green. The colors but not the composition were known to the subjects. The risky (known) urn (K2), had a known composition of yellow and green chips.

With a multiple choice list procedure we asked participants to indicate their preference for a draw from either urn U2 or K2. See Figure 18 for a visualization of the setup.

Figure 18: Choice screen 2-color urn (with <u>green as illustration)</u>

Choice	Option A Urn U2	Your choice:	Option B Urn K2
1		A ○ ○ B	€ 15: 23 chips, €0 otherwise
2		A ○ ○ B	€ 15: 26 chips, €0 otherwise
3		A ○ ○ B	€ 15: 29 chips, €0 otherwise
4	€ 15: (your selected color)	A ○ ○ B	€ 15: 32 chips, €0 otherwise
5	€ 0:	A ○ ○ B	€ 15: 35 chips, €0 otherwise
6		A ○ ○ B	€ 15: 38 chips, €0 otherwise
7		A ○ ○ B	€ 15: 41 chips, €0 otherwise
8		A ○ ○ B	€ 15: 44 chips, €0 otherwise
9		A ○ ○ B	€ 15: 47 chips, €0 otherwise
10		A ○ ○ B	€ 15: 50 chips, €0 otherwise
11	?	A ○ ○ B	€ 15: 53 chips, €0 otherwise
12		A ○ ○ B	€ 15: 56 chips, €0 otherwise
13		A ○ ○ B	€ 15: 59 chips, €0 otherwise
14		A ○ ○ B	€ 15: 62 chips, €0 otherwise
15		A ○ ○ B	€ 15: 65 chips, €0 otherwise
16		A ○ ○ B	€ 15: 68 chips, €0 otherwise
17		A ○ ○ B	€ 15: 71 chips, €0 otherwise
18	Urn U2	A ○ ○ B	€ 15: 74 chips, €0 otherwise
19		A ○ ○ B	€ 15: 77 chips, €0 otherwise
20		A ○ ○ B	€ 15: 80 chips, €0 otherwise

At the start of the experiment, before instructions had been distributed, subjects selected one color: either yellow or green. The number of X chips in urn K2, defined in terms of the participant's selected color, increased in each row (option B), whereas the composition of urn U2 remained unknown and fixed (option A). Each row $i \in (1, 2, \ldots, 20)$ in this list was a separate binary choice between urn U2 and K2. In other words, in each row participants had to choose from which urn they would like to draw a chip: from urn U2 (option A) or from urn K2 (option B). If the chip from the preferred urn was of their selected color, participants won € 15, else nothing (if this choice was randomly selected at the end of the experiment to be played out for real).

The switching point from option A to option B indicates when a subject prefers a draw from urn K2 with X amount of chips in their selected color over a draw from urn U2. If a subject switched to Option B in row i, we take the midpoint between X_{i-1} and X_i chips as an estimate of subjects' matching probability of urn U2. The earlier a participant switches from option A to option B the more ambiguity averse she is.

We refer to an individual's matched probability in the two-color urn setup as m(0.5). For instance, if m(0.5) is 0.38, then a subject indicated to be indifferent between a draw from urn U2 and a draw from urn K2 which is composed of 38 chips in the participant's selected color and 62 chips in the other color. If m(0.5) has a value below 0.5, which is the ambiguity neutral probability of urn U2, ambiguity aversion is expressed. A value of m(0.5) higher than 0.5 indicates ambiguity loving behavior.

We also elicited the matched probabilities m(0.1) and m(0.9), corresponding to the underlying likelihoods of 0.1 and 0.9, by using a 10-color urn. To elicit m(0.1), the unknown urn (U10), contained 100 chips in an unknown composition of 10 colors. Urn K10 on the other hand consisted of a known composition of 100 chips with 10 colors. With the same multiple choice list procedure as before, we measured m(0.1) by letting the participant choose between a draw from urn U10 (option A) or urn K10 (option B). Again, participants knew that they could win € 15 if the chip they draw from their preferred urn was of their selected color, else they won nothing. In each row $i \in (1, 2,...,20)$ the amount X of the chips with the participant's selected color in urn K10 increased. The minimum amount of chips in row 1 (X_1) was 2 chips, and the maximum amount of chips (X_{20}) was 40 chips. The switching point from option A to option B in row i indicated when subjects preferred a draw from urn K10 with X_i chips in their selected color over a draw from urn U10. We again take the midpoint of tokens before and at the switching point, $X_{i-1} + \frac{1}{2}(X_i - X_{i-1})$, as the value of m(0.1). For example, when m(0.1) is 0.16, this indicates that the subject is indifferent between gambling on a draw from urn K10 that is composed of 16 chips in their selected color versus gambling on a draw from urn U10. A matched probability above (below) the ambiguity neutral probability of 0.1 implies ambiguity loving (averse) behavior.

To elicit m(0.9) we run the same protocol as discussed before, only now there are nine winning colors, defined as the nine colors that were not selected by the participant (the complement of urn U10 with 1 winning color). Here X_1 was 60 chips and X_{20} was 98 chips. When m(0.9) is 0.7, for instance, the participant indicated to be indifferent between a draw from urn K10 filled with 70 chips, colored by any of the nine winning colors, versus a draw from urn U10.

For all three list procedures, we designed the program in such a way that participants could only switch once. Subjects who immediately 'switched' to option B in row 1 received the amount of chips in row 1 as their matching probability. At the other extreme, subjects who never switched to Option B received the amount of chips in row 20 as their matching probability. We classified a participant as ambiguity neutral if she switched from option A to option B when the risky urn was in line with the ambiguity neutral probability (for the two-color urn U2 this is row 10 in Figure 1).

AAp refers to the degree of ambiguity aversion for each uncertain event with ambiguity-neutral probability p. We compute the AAp with each individual's matched probability as follows:

$AA_{0.1} = 0.1 - m(0.1)$
$AA_{0.5} = 0.5 - m(0.5)$
$AA_{0.9} = 0.9 - m(0.9)$

We use the method developed by Abdellaoui et al. (2011) to extract two indices: ambiguity aversion and insensitivity. For each participant we estimate the best-fitting line between p and m(p), by means of OLS on the open interval (0,1). We refer to the intercept with c, and the slope with s. Finally, we compute d = 1 – c –s, which is the distance from 1 at the regression line where p = 1 (see Figure 19). Based on these three parameters, we define:

Index a = 1 – s (= c + d), which is the index of insensitivity, and
Index b = 1-s-2c (= d – c), which is the index of ambiguity aversion.

Index b is an anti-index of the average height of the curve and refers to a global index of ambiguity aversion. Index a on the other hand is an anti-index of the steepness of the curve and it reflects the neglect to differentiate between intermediate levels of likelihood and thereby treating these more like a probability of 0.5 (Wakker, 2010; Abdellaoui et al., 2011; Dimmock et al., 2015a).

Figure 19: Indices of ambiguity aversion (index b) and insensitivity (index b) (from Abdellaoui et al., 2011)

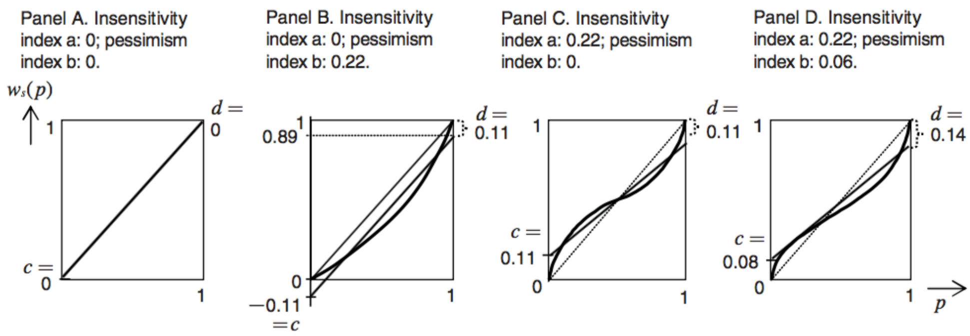


Figure 19 provides an illustration of these indices. In Panel A, the 45° line indicates that the matched probabilities are equal to the ambiguity-neutral probabilities. A participant who can be characterized as such does not exhibit ambiguity aversion or insensitivity. In Panel B ambiguity aversion is expressed with an index b of 0.22, but no insensitivity. Panel C displays insensitivity with an index of 0.22, but no ambiguity aversion. Finally, Panel D shows the most common pattern of both ambiguity aversion and insensitivity with index b = 0.06 and index a = 0.22, respectively.

Consistency

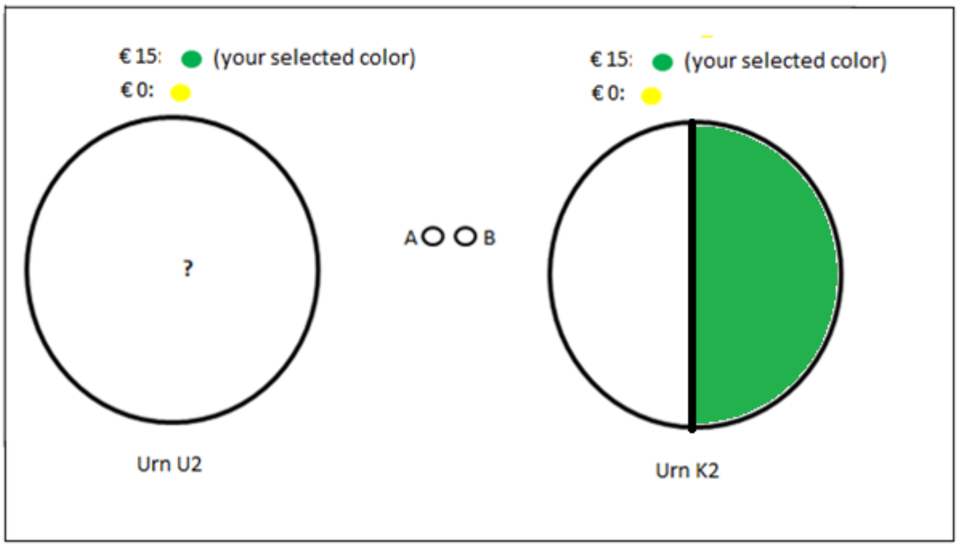
In order to test the consistency of participants' preferences elicited in the multiple choice list, we also administer a direct binominal choice between each of the three ambiguous likelihood events and a risky urn defined by their respective ambiguity neutral probabilities of 0.1, 0.5 and 0.9. Please see Figure 20 for an illustration of the consistency check for the two-color ambiguous urn U2.

This binominal choice was elicited *before* participants were confronted with the choice list procedure. We should observe that a participant expresses similar preferences for either a draw from urn U2 or urn K2 in the direct choice (Figure 20) as in row 10 from Figure 18. The direct comparison between the ambiguous and risky urn allows us to assess the robustness of participants' preferences.

The consistency rates (in percentages of the total participant pool) are 81.97 percent, 76.39 percent and 94.42 percent for the three likelihoods of 0.5, 0.1 and 0.9, respectively. Our consistency rates are higher than Dimmock et al. (2015a; 2015b), and in line with Trautmann et al. (2014). Overall, 69.66 percent (n=136) of our participants showed a consistent pattern for all three likelihoods (henceforth 'consistent sample'). For robustness we rerun all our analyses on our consistent sample. Our findings remain qualitatively intact across both samples (see Models 5 and 6 in Table 9).

Risk attitudes

Figure 20: Choice screen 'consistency check' (with green as illustration)



As risk attitudes positively correlate with borrowing behavior, we also measure individuals' risk preferences to control for this factor (Eckel et al., 2007; Oosterbeek and van den Broek, 2009). Within the same framing as above we elicited subjects' certainty equivalent to a draw from a two-color risky urn (equivalent to K2 with 10 balls and a probability of 0.5). Participants are informed that a drawn marble corresponding to their selected color (yellow or green) would lead to a gain of € 15, else they win nothing.

Participants had to select, in each row in a choice list format of 20 rows in total, their preference between drawing a marble from the risky urn and receiving a sure payoff. The sure payoff increased with each row and reached a maximum amount of € 15 at row 20 (see Task 4 in the instructions in Section 3 of the Appendix). At some point participants switched from choosing the risky urn to the sure option. We take the midpoint of the two sure payoffs before and at the switching point as each participant's certainty equivalent (CE). As a measure of individual risk attitudes we use: $r = 1 - CE/15$ (Wakker, 2010). A value of r larger (smaller), than 0.5, indicates risk aversion (risk loving).

Questionnaire

After we elicited participants' matching probabilities and their attitudes towards risk, we administered a questionnaire. We specifically asked if they were familiar with DUO before they answered subsequent questions. All students were well aware of the existence of DUO.

The questionnaire consisted of three parts (the complete questionnaire can be found in Section 3 of the Appendix). Part 1 of the questionnaire dealt with questions concerning their borrowing behavior. The main questions we use for our analyses ask whether or not they borrow, and if so, how much they borrow. In part 1 we also conducted a cognitive reflection test (Frederick, 2005) and a financial literacy test (Lusardi and Mitchel, 2006). Both these tests contained three questions and each participant received a normalized score between 0-1 depending on the amount of correct answers.

Part 2 of the questionnaire included demographic questions such as age, gender, living situation, study year and study topic.

The last part of the questionnaire, part 3, was the life orientation test, which measured general optimism and pessimism (Scheier and Carver, 1985; Scheier et al., 1994). Participants indicated on a 5-point Likert scale (scored with a range from 0-4) if they totally (dis)agreed with the statement being posed. A maximum score of 24, respectively 0, means an extremely optimistic and pessimistic view on life.[32]

Procedures

The experiments were conducted at NSM laboratory (Nijmegen School of Management) at the Radboud University Nijmegen and ELSE (Experimental Laboratory for Sociology and Economics) at the University of Utrecht in March 2014. 233 participants - 130 females and 103 males - participated in our study. The experiments were computerized using the software z-Tree (Fischbacher, 2007). All participants had to answer comprehension questions before each task. We checked their answers and, in case of mistakes, privately explained the correct answer before all participants were allowed to start the task.

There was a fixed order of tasks. The matched probabilities were elicited in the following order: m(0.5), m(0.1) and m(0.9). This is in line with procedures from Dimmock et al. (2015a; 2015b). Subsequently we elicited participants' risk preferences. Finally participants filled in the questionnaire before any feedback was given on the results and payment of the experimental tasks.

Participants received a sure amount of €4 as show-up fee. At the end of each session the computer would randomly select one choice from one of the four experimental tasks: one row from one of the choice lists used to elicit the matching probabilities of the ambiguous likelihood events of 0.1, 0.5 and 0.9 and participants' risk preferences. This randomly selected choice was played out for real by letting participants select a chip from either urn U2, urn U10 or from a risky urn. If a participant would have to draw a chip from the risky urn, we would compose an 'urn' in front of their eyes by filling it with the

[32] We added this part to the questionnaire as we were interested to study if the optimism and pessimism scores from this life orientation test would correlate with the optimism and pessimism labels used to describe overweighting of low likelihoods, respectively underweighting of high likelihood events (See Table A7 of the Appendix). As scores on the life orientation test had no relationship with borrowing behavior, we do not report them in our main results section.

amount of chips in their selected color (corresponding to the selected row).

Subjects were paid, in cash and in private, €12.15 on average (including show-up fee) for a session lasting about one and a half hour

The production of the unknown urns U2 and U10 was explained very carefully at the start of the experiment. We used four different production methods to construct urns U2 and U10, namely 'human', 'compound', 'unknown' and 'nature'.[33] During the whole experiment urn U2 and urn U10 were visibly placed in the laboratory so that any suspicion participants could have had with regard to potential manipulation of the ambiguous urns was eliminated. The instructions of the experiment can be found in the Appendix.

Results

Sample descriptives

We excluded five participants from our total set of 233 participants. Three participants turned out not to be a student in violation of our selection criteria. Two participants did not report their income, which we use as a control variable in our analyses. All analyses are conducted with the remaining 228 participants.

Table 5 shows that 33 percent of our subjects borrow money at DUO on a monthly basis. The average amount borrowed is €388,16 per month.[34] Both these figures are very consistent with findings from much larger representative samples (Biermans et al., 2003; van den Broek and van de Wiel, 2005; Oosterbeek and van den Broek, 2009;

[33] The four production methods were implemented as four separate treatments randomized over 17 different sessions in a between-subjects design. In a companion paper we focus on the question if ambiguity attitudes are influenced by the construction of an ambiguous urn. All results in this paper remain qualitatively valid when including dummies for either sessions or for production methods in our statistical models. Please see our Appendix for a more detailed explanation of the production methods and for the results of the robustness analyses (Table A9).

[34] This amount is higher than the maximum of €301,27 per month, because many students study longer than four years, after which they can borrow up to €916,96 (see Section 2 of this Chapter).

Nibud, 2012). Table 5 also shows that borrowers live more frequently on their own, have higher living expenses, more siblings, are further progressed in their study, and older than non-borrowers ($p<0.05$, two-sample t-test). Also, the total amount of income is higher for borrowers than for non-borrowers; this may indicate that borrowers need to offset higher living expenses.

Table 5: Frequencies for borrowers versus non-borrowers

Variables:	Borrowers	Non-borrowers	Overall
	32,62%	67,38%	100%
Income	€ 661,04	€ 556,88	€ 602,10
Age	21,92	21,05	21,68
Siblings	1,83	1,61	1,674
Female	56,58%	55,41%	55,79%
Economics study	9,21%	24,20%	19,31%
Live on own	85,53%	70,70%	75,54%
Amount borrowed	€ 388,16	€ 0	€ 126,61

Ambiguity attitudes

Table 6 shows that, on average, subjects have matching probabilities below the ambiguity neutral probabilities of 0.5 and 0.9 and overweight the ambiguity neutral probability of 0.1. This pattern is both consistent with ambiguity aversion (mean index b value of 0.097, which is significantly higher than 0: $t(227)=13.235$, $p<0.001$) and insensitivity (mean index a value of 0.254, which is significantly higher than 0: $t(227)=22.712$, $p<0.001$).

In Table 7 the percentages of participants who can either be classified as ambiguity averse, neutral or seeking are distinguished for the three different likelihoods. In coherence with a positive value of insensitivity, the percentage of ambiguity averse (seeking) participants increases (decreases) in the ambiguity neutral probability.[35]

[35] Please see Table A8 in the Appendix for more descriptive data on ambiguity attitudes.

Table 6: Ambiguity attitudes				
Variable	Mean	Std. Dev.	Min	Max
MP01	0.142	0.064	0.02	0.40
MP05	0.475	0.083	0.23	.8
MP09	0.738	0.110	0.60	.98
AA01	-0.042	0.065	-0.30	0.08
AA05	0.025	0.083	-0.30	.27
AA09	0.162	0.110	-0.08	.3
Index b (ambiguity aversion)	0.097	0.110	-0.45	.31
Index a (insensitivity)	0.254	0.169	-0.2	.89

Table 7: Ambiguity attitudes for each likelihood			
	Ambiguity neutral probabilities		
Ambiguity attitude	0.1	0.5	0.9
Ambiguity averse	13 (6%)	87 (38%)	197 (86%)
Ambiguity neutral	59 (26%)	76 (33%)	20 (9%)
Ambiguity seeking	156 (68%)	65 (29%)	11 (5%)

Ambiguity attitudes and borrowing behavior

In order to test if ambiguity attitudes influence the decision to take out a student loan, we first run a logistical regression model with the borrowing decision as dependent variable. This dependent variable is a dichotomous variable, with 1 indicating if a student borrows, irrespective of how much, and 0 indicating when a student does not borrow. We find marginally significant ($p<0.1$) trends of financial literacy, studying economics, and whether one lives on her own on the decision to borrow (Table 8). Both ambiguity aversion and insensitivity, however, do not influence the decision to take out a student loan.

Please recall from Table 1 that 33 percent of our subjects borrow money monthly at DUO. Subsequently we analyze the role between ambiguity attitudes and the amount borrowers ($n=76$) in our student population borrow. A Pearson product-moment correlation shows a significant negative correlation between ambiguity aversion (index b) and the amount a student borrows ($r=-0.235$, $p<0.05$).

Table 8: Logistical regression ambiguity attitude on borrowing behavior

Do you borrow	1	2	3	4	5	6
Index b	0.657 (1.424)	0.424 (1.481)			2.080 (2.351)	
Index a	0.176 (0.941)	0.145 (0.956)			-0.150 (1.294)	
AA0.1			-1.419 (2.473)	-1.939 (2.514)		-2.841 (3.784)
AA0.5			2.007 (1.946)	2.211 (1.972)		5.900* (3.234)
AA0.9			0.070 (1.396)	-0.278 (1.463)		-0.334 (2.014)
Risk aversion		-1.108 (1.143)		-1.111 (1.148)	-1.188 (1.519)	-0.270 (1.546)
Financial literacy		-.449* (0.257)		-0.487* (0.261)	-.415 (0.345)	-0.447 (0.351)
Cognitive reflection test		-0.126 (0.449)		-0.094 (0.451)	-1.070* (0.543)	-1.073 (0.664)
Income	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Study years	0.049 (0.062)	0.051 (0.063)	0.051 (0.062)	0.053 (0.063)	0.057 (0.089)	0.053 (0.092)
Female	0.021 (0.305)	-0.056 (0.317)	0.031 (0.306)	-0.048 (0.319)	-0.769* (0.447)	-0.791* (0.456)
Economic study	-1.070** (0.450)	-0.803* (0.470)	-1.067** (0.451)	-0.788* (0.470)	-1.543** (0.713)	-1.512* (0.713)
Siblings	0.095 (0.122)	0.073 (0.126)	0.083 (0.122)	0.058 (0.126)	-0.047 (0.169)	-0.058 (0.170)
Live on own	0.704* (0.406)	0.732* (0.414)	0.728* (0.408)	0.762* (0.415)	1.603*** (0.611)	1.728*** (0.622)
Constant	-1.694 (0.538)	0.020 (0.984)	-1.710 (0.541)	0.074 (0.992)	-1.556 (0.699)	0.074 (1.305)
Observations	228	228	228	228	136	136
Consistent sample	0	0	0	0	1	1
LR Chi2	chi2(8) = 17.26	chi2(11) = 21.90	chi2(9) = 18.13	chi2(12) = 23.20	chi2(8) = 18.61	chi2(11) = 23.50
Prob > Chi2	0.0276	0.0251	0.0337	0.0261	0.0171	0.0150
Pseudo R-squared	0.0595	0.0755	0.0624	0.0799	0.135	0.0799

****,**,* significant at the 0.01, 0.05, 0.1 respectively. Standard errors reported in parentheses.*

We also run an OLS regression with the amount borrowed (on a monthly basis) as dependent variable (Table 9). We created two interaction variables by multiplying the dichotomous variable if one borrows (indicated by 1) or not (indicated by 0) with each of the two ambiguity attitudes indices. The variables Borrow*Index b and Borrow*Index a in Table 9, respectively, indicate the values of ambiguity aversion and insensitivity for all borrowers in our student population. The previously found negative bivariate relationship between borrowers' ambiguity aversion and the amount they borrow remains significantly valid in a multivariate setting (Table 9). For robustness we performed the same analyses with the consistent sample (see models 5 and 6 in Table 9). The negative relationship between ambiguity aversion and the amount borrowed also holds when considering only the consistent subsample.

Finally, in the Appendix we report several other robustness analyses. We include all sessions separately as dummy variables in our regression models, as well dummies for the different production methods of the ambiguous urn we employed in our study (Table A9 Appendix). All our reported results remain qualitatively stable: the more ambiguity averse a student is, the less she borrows.

Table 9: OLS regression ambiguity attitudes on amount borrowed

Conditional borrowers						
Amount borrowed						
	(1)	(2)	(3)	(4)	(5)	(6)
Index b	69.997		59.722	63.559	17.254	59.275
	(107.294)		(112.687)	(115.408)	(142.137)	(144.019)
Index a		34.324	22.232	28.798	21.845	35.802
		(69.351)	(70.459)	(71.536)	(88.583)	(89.352)
Do you borrow	443.174***	387.623***	416.653***	419.472***	391.531***	401.303***
	(26.165)	(37.183)	(36.838)	(37.393)	(44.337)	(44.869)
Borrow*IndexB	-585.332***		-639.012***	-625.027***	-432.489*	-425.392*
	(171.341)		(180.191)	(182.623)	(247.077)	(247.506)
Borrow*IndexA		-15.514	122.643	111.277	9.155	-3.814
		(120.143)	(122.225)	(123.700)	(151.779)	(152.958)
Risk aversion				-22.966		-69.405
				(71.633)		(84.632)
Financial literacy				11.958		20.016
				(16.001)		(19.459)
Cognitive reflection test				-4.624		49.301
				(27.569)		(35.555)
Income	-0.055*	-0.046	-0.050*	-0.053*	-0.034	-0.038*
	(0.029)	(0.030)	(0.029)	(0.030)	(0.032)	(0.033)
Study years	11.501***	10.805***	11.462***	11.288***	6.117	4.733***
	(4.042)	(4.167)	(4.046)	(4.091)	(5.178)	(5.245)
Female	-14.213	-24.709	-15.641	-14.543	-11.918	0.286
	(18.936)	(19.457)	(18.949)	(19.597)	(23.917)	(25.088)
Economic study	50.274**	45.811*	52.417**	48.084*	34.577	25.847*
	(23.838)	(24.571)	(23.881)	(25.086)	(30.203)	(31.610)
Siblings	15.547**	12.457*	15.631**	15.487*	4.239	4.011
	(7.880)	(8.116)	(7.883)	(7.980)	(10.198)	(10.251)
Live on own	44.555*	44.951*	41.504*	41.867*	17.615	13.368
	(23.161)	(24.145)	(23.376)	(23.525)	(30.264)	(30.474)
Constant	-58.026	-72.712	-51.996	-62.338	-63.184	-76.636
	(30.475)	(62.197)	(33.838)	(64.594)	(33.560)	(63.742)
Observations	228	228	228	228	136	136
Consistent sample	0	0	0	0	1	1
F test	F (9,218) = 49.17	F(12,215) = 36.56	F (9,218) = 44.46	F(12,215) = 33.39	F(11,216) = 40.49	F(14,213) = 31.51
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Adjusted R-squared	0.656	0.653	0.657	0.653	0.608	0.609

****,**,* significant at the 0.01, 0.05, 0.1 respectively. Standard errors reported in parentheses.*

Discussion and conclusion

This study is part of a relatively new stream in decision research that attempts to relate experimentally elicited ambiguity attitudes to real life decision-making outside the laboratory. Contrary to our hypothesis we do not find a relationship between ambiguity attitudes and borrowing behavior. We find a weak effect between ambiguity aversion and borrowing behavior by showing that ambiguity aversion affects the amount a student borrows: the less ambiguity averse students are more willing to borrow. We do not find any relationship with insensitivity, which may be due to the fact that the most extreme event, total default, is not very rare (Figures from Dutch Ministry of Education, 2014).

Ambiguity preferences affect the amount a student borrows, but not the decision to borrow at all. This finding is in line with other studies. For instance, Dimmock et al. (2015a) only find a statistically significant relationship between ambiguity aversion and stock market participation when considering participants with a minimum amount of $500 in financial assets. Also, ambiguity preferences affect the amount a person plans to save for retirement planning, but ambiguity preferences do not influence the initial decision whether to plan for retirement or not (Dimmock et al., 2015b). As our results show a similar pattern, more research is needed to disentangle the factors that determine the loan amount from those that determine whether a loan is taken out at all.

As discussed in section 2 of this Chapter, the cohort of students that participated in our study receive(d) a basic scholarship from the government along the possibility to take out a study loan. As the Dutch government faces pressures to reduce costs, fewer resources are allocated to education. One of the recent consequences is that the cohort of Dutch students who started in September 2015 did not receive a monthly basic scholarship and will have to exclusively rely on student loans. This will make a less ambiguous and more cost-transparent design of the student loan allocation even more important.

From countries with higher educational fees, results show that students, who are reluctant to borrow, choose more frequently to work part-time or opt for a lower cost institution, or study part-time (Institute for Higher Education Policy and Excelencia in Education, 2008). These are all factors that increase the risk of study dropout. Next to this potential risk of higher dropout rates, a 2.1 percent decline in the amount of Dutch students pursuing higher education is predicted as a consequence of this new policy (SEO Economic Research, 2014).

How can we utilize the relationship between ambiguity aversion and the amount a student is willing to borrow in order to avoid these negative consequences? Easley and O'Hara (2009) show that regulation, especially when focused on worst-case scenarios, can moderate the effects of ambiguity aversion on non-participation on stock markets. They show, theoretically, that investors, who are guaranteed that worst case scenarios cannot materialize, for example by introducing deposit insurance and guarantees, are more likely to participate. Such a legal regulation guarantees that no matter what, investors will always receive their money back. As we can assume that most graduates have an intrinsic as well as an extrinsic motivation to find the best paying work after they finished their studies, it is unlikely that such a bailout regulation will be abused strategically.

The worst-case scenario for a student deciding on taking out a student loan is that she will not be able to repay the debt. An explicit guarantee that the government will act as a last resort could be installed to reduce ambiguity. As our results tentatively show, this would increase students' willingness to borrow for secondary education and potentially improve study results and speed by reducing negative effects of part-time jobs. Secondly, uncertainty can be greatly diminished by introducing more stable future interest rates. Future research is needed to test if this and other regulatory measures would actually diminish the effect of ambiguity aversion on borrowing and study success.

Chapter 6

The uncertain adolescent[36]

Correlates of self-confidence and preferences for risk and ambiguity in adolescents

Introduction

Uncertainty is an integral part of our day-to-day decisions. In some (relatively rare) situations we possess clear information about the likelihood of the various outcomes of a particular choice, for instance the probability that it will rain in the coming hour and we will get wet when biking home. However, most of the typical choice scenarios we confront require that a decision be made without having access to such clear probabilities, for instance, to give another weather-related example, if you should plan your next month's birthday party outside or arrange for alternative indoor arrangements in case of bad weather. In economics, the distinction between choices made with known and unknown probabilities have been labeled as 'risky' and 'ambiguous' choices respectively (Trautmann and van de Kuilen, 2013).

In a now classic demonstration, Ellsberg (1961) showed that majority of people demonstrate ambiguity aversion, that is, a preference for betting on a risky rather than on an ambiguous prospect, when each option possesses equivalent SEUs (Savage, 1954)[37] Subsequently, theoretical models have attempted to incorporate ambiguity aversion in order to explain particular choice anomalies that previously could not be accounted for adequately using SEU (Easley and O'Hara, 2009; Guidolin and Rinaldi, 2009; Uppal and Wang, 2003; Liu,

[36] This chapter is based on a joint paper with Alan Sanfey, The uncertain adolescent. Correlates of self-confidence and preferences for uncertainty in adolescents, 2015, under review.
[37] See Box 1 and 2 in the Introduction for a detailed explanation of both the experimental setup by Ellsberg (1961) as well as SEU.

2011; Alary et al., 2013; Snow, 2011). Experimental laboratory studies on the other hand have focused on moderators of both risk and ambiguity aversion (see the Introduction for examples of such moderators). One such moderator, the comparative ignorance hypothesis, stresses how ambiguity aversion is affected when elicited in isolation or directly in comparison to risk (Qiu and Weitzel, 2011). In experimental laboratory studies on ambiguity, this moderator should be taken into account as it influences individual scores for ambiguity depending on the order in which risk and ambiguity are elicited. We will discuss this moderator and its effect on our results in greater detail in the discussion. Furthermore, experimental studies have extensively examined the correlation between risk and ambiguity and primarily found a positive correlation between both constructs (Kocher et al., 2015; Vieider et al., 2012; Abdellaoui et al., 2011; Heath and Tversky, 1991; Tversky and Fox, 1995).

While these theoretical and experimental results are interesting and informative, there has been much recent interest in extending our knowledge beyond the laboratory and examining choices made in the real world. This is important as theoretical literature on real-life anomalies, such as why people do not participate in the stock market as much as theory would predict, refer to experimental evidence on ambiguity to motivate an alternative theoretical explanation based on ambiguity aversion. As there is surprisingly little evidence supporting a relationship between experimentally elicited ambiguity preferences and behavior outside the laboratory (see Chapter 6 for an overview of these studies), exploring the external validity of ambiguity is a worthwhile endeavor (Trautmann and van de Kuilen, 2013). In addition to lacking a real-life context, the laboratory studies typically explore these choice preferences in the population of university undergraduate students, which naturally reduces socio-demographic variation (von Gaudecker et al., 2011).

In contrast to ambiguity, the external validity of risk preferences has received some attention (Dohmen et al., 2011; Einav et al., 2012; Lauriola et al., 2007; Pennings and Smidts, 2000; Vieider et al., 2014; Tanaka et al., 2010; Liu and Huang, 2013; Cole et al., 2013; see Introduction for an overview of these studies). Some of these studies have also been conducted with non-student populations, for instance studying people living in developing countries (Vieider et al., 2014; Tanaka et al., 2010; Liu and Huang, 2013; Cole et al., 2013). Whereas results of some studies (Dohmen et al., 2013; Vieider et al., 2014) demonstrate stability of individual risk preferences across various decision domains, other studies (Weber et al., 2002; 2006) have shown that individual risk preferences are domain specific. This means that one study proposes that context-specific risks such as health, financial or recreational risks should be captured separately (Weber et al., 2002), whereas at the other spectrum, one study proposes the existence of one underlying 'risk preference', which should capture behavior towards risks independently of its corresponding choice domain (Vieider et al., 2014).

In summary, we believe that more research is needed to address if, and under which circumstances, individual risk preferences are domain-specific and subsequently what the implications are for understanding real-life decision-making. Moreover, as most uncertainties in life are of an ambiguous rather than a risky type (Post et al., 2008), empirical studies could usefully explore both types of uncertainty as potential underpinnings of choice behavior. Indeed, acknowledging both risk and ambiguity is important in order to pinpoint which type of uncertainty affects the specific decision domain under investigation. For example, when only considering risk preferences, previous research (Oosterbeek and van den Broek, 2009) found a positive relationship between risk aversion and students' borrowing behavior. However, as shown in the previous Chapter, we could not identify a relationship between risk preferences and students' borrowing behavior when both risk and ambiguity were included as independent predictors of students' borrowing behavior.

Taken together therefore, it would be a useful endeavor to explore risk and ambiguity in more detail, and also to extend the investigation of risk and ambiguity, in particular preferences for ambiguity, to both a broader sample and to more ecologically valid decisions. In the current paper we address both of these aims, by examining the external validity of risk and ambiguity outside the laboratory by using a sample of non-university students. Specifically, we focused on adolescence, a phase of life beginning around the onset of puberty and ending when an individual achieves adult-like levels of independence (Somerville, 2013).[38] Adolescents are often confronted with serious decisions with uncertain outcomes, and, more often than any other age group, this cohort engages in risky behavior such as drinking, smoking, unprotected sex, criminal activities and reckless driving (Steinberg, 2004; Tymula et al., 2012; Blum and Nelson-Mmari, 2004; Williams et al., 2002).

Given the clear societal importance of examining decision-making in this age group, adolescents' risk preferences have been previously studied (Reyna and Farley, 2006; Steinberg, 2004, 2008; Harbough et al., 2002; Levin et al., 2007). However, and importantly, the role of ambiguity in adolescents has received far less attention (see Tymula et al. (2012) for a notable exception). To the best of our knowledge, only Sutter et al. (2013) has explored the relationship between risk/ambiguity and real-life behavior of adolescents, with this study focusing on health related behavior, such as drinking and smoking. Though this latter behavior is indeed important, we wanted to extend the research to an examination of a different, yet equally relevant, aspect of health, namely mental health. Specifically, we focus here on the concept of self-confidence. Low self-esteem in adolescents, which is a product of low self-confidence, is found to be an important predictor of psychological problems such as suicidal ideation (McGee and Williams, 2000), criminal behavior, and limited economic prospects (Trzesniewski et al., 2006) later in life.

The concept of self-confidence is comprised of self-belief regarding one's own capabilities and one's social standing. The latter component in particular is a defining feature of this period, as adolescents have a strong desire for social relatedness and are highly sensitive to information concerning social evaluation and social standing (Somerville, 2013). At the same time, social complexity has dramatically increased with the rise of digital communication (Pfeifer et al., 2013). Adolescents spend relatively less time with their families, more time with their peers, and digital peer communication peaks at this age (Larson, 2001; Lenhart et al., 2010). Although adolescents spend a lot of time with their peers, either in real life or virtually, these

[38] Typically, the age range of adolescence is between 10 and 19 years (World Health Organization, 2014).

relationships are quite labile. Friends come and go, and adolescents will experience peer rejection more often compared to other age groups (Wang et al., 2009).

Overall, adolescents care about their social relationships and their social standing amongst their peers. Adolescents' social relationships are rather unstable however. As self-confidence is partly shaped by how individuals evaluate their social standing, we are interested therefore in exploring if risk and ambiguity, as measured via standard economic elicitation techniques, capture some of the uncertainty inherent in adolescents' peer-to-peer relationships. Specifically, we examine if risk and ambiguity aversion in adolescents transcend to another domain of uncertainty, namely one's self-belief in social standing and own capabilities. We hypothesize that those adolescents who dislike uncertainty most, that is, who are more risk and ambiguity averse, will at the same time express more uncertainty concerning their social standing and self-belief regarding their own capabilities.

So far we have focused on risk and ambiguity as types of uncertainty and stressed the importance to address the external validity of these constructs in adolescents. In this study we also propose to empirically examine the construct of prudence in this group.

Prudence is a higher order risk attitude which can be operationalized as the sign of the third derivative of the utility function. A positive third derivative can be interpreted as reperesenting prudent behavior, implying precautionary saving, that is, greater savings in response to an increase in background risk (Kimball, 1990; Noussair et al., 2013). This concept has been linked to economic applications such as bargaining (White, 2008), sustainable development and climate change (Gollier, 2011), and tax compliance (Snow and Warren, 2005). Similarly to risk and ambiguity, these theoretical insights are not supported to date by much empirical validation. A notable exception is a recent paper by Noussair et al. (2013) which found evidence of prudence in both the general population as well in a sample of students. In line with theoretical predictions, they found a positive relationship between prudence and general wealth, for example, a greater likelihood of possessing a savings account and a lower likelihood of having credit card debt. Interestingly, students were especially prudent, with education levels being positively correlated with prudent behavior. These findings are in line with our empirical results from the previous Chapter, where we showed that students in the Netherlands would rather opt for a part-time job to increase their saving and spending possibilities than borrow money (see Chapter 5). Though such behavior is suggestive of prudent behavior, to date no studies have specifically examined higher order risk attitudes in adolescents.

We believe prudence is an important concept to explore in adolescents. Adolescents will be confronted with managing their own budget for the first time in their lives, that is, during adolescence they typically experience a transition from high school to college or the workforce, and this often forces them to think more carefully about their spending and savings behavior. As Sutter et al. (2013) found a positive correlation between intelligence and saving behavior in their adolescent population, we will examine if prudence is one of the underlying explanatory drivers.

As a first investigation of prudence and adolescence, in this study we aim to examine if prudence is a construct that is already present at a young age, and to what extent it correlates with demographic characteristics. These insights could potentially identify those adolescents who may be vulnerable to taking on too much debt or who are not likely to take out a student loan when they start studying after they finished high school (see Chapter 5 for implications).

To answer this set of research questions, we recruited a large sample of adolescents (aged 12 to 17) from a high school in Nijmegen, The Netherlands. We elicited risk and ambiguity preferences via a standard Ellsberg lottery setup (Ellsberg, 1961), and subsequently examined preferences for prudence via a model free measurement approach as per Eeckhoudt and Schlesinger (2006). We also investigated adolescents' attitudes towards losses, as this could be an important factor driving adolescents' attitudes in social relationships. Finally, we employed the cognitive reflection test as a construct of cognitive ability (Frederick, 2005). Our participants also completed a set of validated questionnaires that provided individual scores for measures such as intelligence, motivation, and well-being (Liepmann et al., 2007; Smits and Vorst, 2008). Our primary interest in this regard was the construct of self-confidence. The questions on self-confidence capture important aspects of adolescents' social sensitivity, as well as measuring self-belief in their own capabilities.

In summary, this study examined the role of adolescents' risk and ambiguity preferences in their self-belief of their own capabilities and social standing. Additionally, we explored adolescents' attitude towards the higher order risk concept of prudence and related this to adolescent's demographics.

Methods

Participants

We conducted this study with 187 adolescents at a high school in Nijmegen, The Netherlands. This paper and pencil experiment took place over the course of one week in May 2014. The responsible local ethics committee approved this study.

Two classes per school-year were randomly selected, with participants' age ranging from 12-17 years. We excluded the first and last school year as the former had been recently exposed to the intelligence test and psychological measures, and the latter were preparing for their final school exams. We organized the experiment during regular school hours in the 'mentor class'. This is a weekly class hour especially dedicated for the class mentor to inform pupils about school news, to discuss class matters, and talk to pupils individually.

The mentors of the selected classes informed the parents of the participants about the upcoming experiment via an information letter. In order for their child to participate, parents were required to return a signed statement (opt-in consent). They could either return this to the mentor, or they could send an email to the researchers along with any questions they might have.

In total, we tested 187 participants during regular school hours. As there were missing data from 15 participants, we excluded them from our sample. This left us with a total of 172 participants (83 girls and 89 boys). All the results we present in the next section are based on these 172 participants.

Experimental design

Participants completed experimental tasks in their classroom. First we elicited risk and ambiguity preferences, followed by an assessment of their beliefs regarding the ambiguous prospect. We also estimated parameters for prudence and loss aversion. Finally, participants completed the three questions on the cognitive reflection test (Frederick, 2005). The instructions (in Dutch) can be found in the Appendix.

Risk and ambiguity

We elicited risk and ambiguity preferences via a multiple-choice list procedure, as per Sutter et al. (2013). In both the risky and ambiguous settings, participants chose on each trial between a gamble and a sure pay-off, with the latter increasing in size after each choice.

Risk and ambiguity were induced via a standard Ellsberg setup (Ellsberg, 1961). In our version there were two (actual) bags, which were both filled with 20 ping-pong balls. One bag, the risky prospect, was filled with exactly 10 orange and 10 white ping-pong balls. The other bag, the ambiguous prospect, was filled with an unknown composition of white and orange ping-pong balls. Beforehand, participants chose either white or orange as 'their' color, with this choice determining the specific ping-pong ball color that would lead to a win for them. A gamble in this setting meant that a participant would draw a ping-pong ball from the bag. A participant won 5 Euro if this ping-pong ball matched the color she selected beforehand, otherwise she would win nothing. It was important that participants could choose their own winning color in order to (correctly) eliminate any suspicion that the likelihood of a win/loss from the ambiguous bag may have been predetermined (Wakker, 2010).

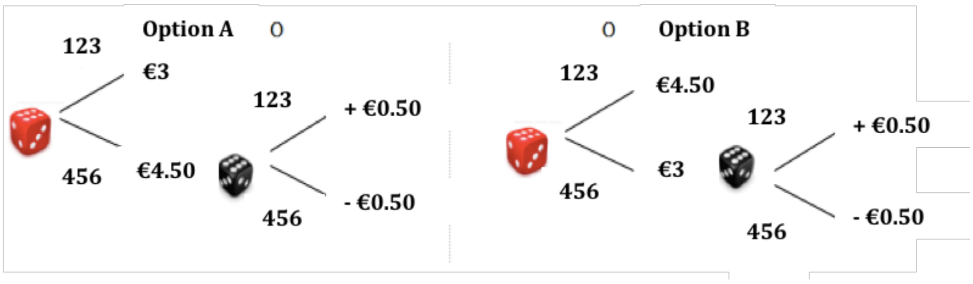
For both risky and ambiguous prospects, participants saw a total of 20 choices each. Each choice was between gambling on the draw of a winning colored ping-pong ball from the bag, or receiving the sure pay-off. The sure pay-off increased from 0 to 5 Euro in 20 equal steps of 0.50 Euro. We observed when participants switched from the gamble to the sure pay-off. The later they switched to the sure pay-off, the more they were willing to gamble, and therefore the less they expressed risk/ambiguity averse behavior. The choice lists for the risky and ambiguous prospect were counterbalanced across different class groups to control for any potential order effect.

After participants made their decisions for the ambiguous prospect, we elicited their beliefs regarding the composition of the ambiguous bag. Specifically, we asked them to indicate how many ping-pong balls they thought were present in the ambiguous bag, which were colored in their selected color. As there are a total number of 20 ping-pong balls in the ambiguous bag, which have a color from a set of only two potential colors, the objective underlying likelihood to draw a ping-pong ball that matches participants' selected color is 0.5, which boils down to 10 ping-pong balls that match participant's selected color. Any difference participants report in their expectation that 10 ping-pong balls will have a color matching their selected color indicates a deviation from the ambiguity neutral state.

Prudence

We estimated preferences for prudence via a number of decision problems that do not require any axiomatic assumptions concerning the utility function. Specifically, we elicited a measure of the construct of prudence using a model-free method that defines prudence as a preference for adding a lottery with a mean of zero to a state in which income is high, rather than adding it to a state in which income is low (Eeckhoudt and Schlesinger, 2006; Noussair et al., 2013). See Figure 21 for an illustration of one choice setup. The original monetary amounts used in this task were scaled down to appropriate monetary amounts for adolescents. In this example (Figure 21) the decision maker faces two problems, which are the possibility to win less (a reduction of wealth by 1.50 Euro) and the possibility to face a zero-mean lottery. A prudent decision-maker prefers to disaggregate both harms (Rothschild and Stiglitz, 1970), therefore she would opt for Option A in Figure 21. The five decision problems presented to participants were similar in structure to Figure 21, but varied in terms of the initial endowment and the wealth reduction (lottery attached to the red dice in Figure 21), and the size of the zero-mean lottery (lottery attached to the black dice in Figure 21). Each participant received a score for prudence based on the number of prudent choices she made. A score of 0 implied extreme imprudence, whereas a score of 5 implied extremely prudent behavior. We assessed the level of prudence in our population by relating participants' score for prudence compared to a score of 2.5, a score that indicates indifference (Noussair et al., 2013).

Figure 21: Example decision problem prudence measurement



Loss aversion

Our elicitation method for loss aversion was based on the choice list procedure developed by Fehr and Goette (2007). We scaled down the original monetary amounts to appropriate amounts for our experimental sample. This task consisted of six decision problems. Each decision problem was a binominal choice between playing a gamble and a status quo of 0 Euro. The gamble involved a 50 percent chance to win 2.25 Euro and a 50 percent chance to lose an amount x. This negative amount x increased from -0.25 to -2.75 Euro in equal steps of 0.50 Euro. The more often the participant refrained from playing the gamble, the more we infer she disliked the potential loss. This number was the individual measure of loss aversion. We compared participants' score for loss aversion to a score of 3, which score would indicate random choice.

Questionnaire data and auxiliary measures

The high school provided us with a large set of auxiliary measures. Firstly, we received basic demographic data, such as age and gender, as well as participants' grades for all courses as listed on their most recent semester report. Secondly, the high school provided scores on a set of validated intelligence tests and psychological measures. All pupils take these tests in the first year at this high school, with pupils that score above average on the intelligence test offered an extra curricular program. Pupils who score low on psychological measures like self-confidence are offered specific training or receive more individual support from their class mentor.

The school used the 'IST Intelligence Structure Test' (Liepmann et al., 2007), which provides a score for six subdomains of intelligence, namely: general intelligence, memory, general development, verbal intelligence, numerical intelligence, and abstract intelligence, as well as a total average score of intelligence. We used the scores for verbal reasoning, numerical reasoning, abstract reasoning and the total intelligence score in our analyses.

The psychological test is a validated questionnaire of 160 statements in which pupils have to rate the extent to which the posed statements are similar to their character/behavior (Smits and Vorst, 2008). The outcome is a score on three domains, namely self-confidence, well-being, and motivation, with these domains divided into sub-domains. For self-confidence, these sub-domains are the ability to express oneself in a social environment, confidence in taking exams, and social skills. For well-being, the sub-domains are whether pupils enjoy school, feel accepted at school, and how they value the relationship with their teachers. Finally, motivation is captured by study focus, concentration in the classroom, and attitude towards homework. In our analyses we first planned to use the overall scores for self-confidence, well-being, and motivation. If we identified a significant relationship between our experimental variables and these psychological main scores, we further analyzed the individual sub-domain scores that comprised the overall score in each domain.

Lastly, we conducted the cognitive reflection test (CRT; Frederick, 2005). This test contains three questions, which proxy cognitive capabilities. For instance, one such question is the following: a bat and a ball together cost 1.10 Euro in total. The bat costs 1 Euro more than the ball. How much does the ball cost? The natural tendency is to answer with 0.10 Euro, yet the correct answer is 0.05 Euro. The other two questions similarly pose cognitive load to inhibit the natural tendency to answer quickly and intuitively. Each participant received a normalized score between 0-1 depending on the amount of correct answers.

Procedures

Each participant listed their school ID number on their set of instructions. On the basis of this ID number the school provided the individual participant's data, as outlined above. The link between ID number and participant's identity was unknown to us, and additionally the school did not receive our experimental data. In this way we could guarantee participants complete anonymity in this experiment.

At the start of the class, all participants were seated in an exam-style format whereby they could not directly look at their neighbor's table. We extensively trained two research assistants who conducted the experiment in the classrooms. One would read the instructions aloud in front of the classroom. Any questions participants asked for clarification, were publicly discussed. Each experimental task would only start after everything was clear and the clarification questions given for each experimental task were correctly answered.

One randomly selected decision from one randomly selected task was played out for real after the participant's last school class. We decided to randomly select one choice on each test day that would determine the payoff of all participants who participated in the experiment on that specific day. On average our participants earned a total of 5.42 Euro for an experiment lasting 50 minutes.

If a choice from the risky or ambiguous prospect was randomly selected to determine the payoff, participants' decisions were played out in the following way. If they had decided to gamble they could themselves draw a ping-pong ball from the corresponding bag. The color of the ping-pong ball determined a win or a loss. If they had opted for the sure payoff, this corresponding amount was immediately paid out to them without further action. If one choice from the prudence task were to be played out for real, participants had to roll a die twice in a row for the specific gamble they had chosen. Finally, if one choice from the loss aversion task was selected, participants flipped a coin if they had decided to play the gamble in that specific choice. They could state if they would rather bet on head or tails to receive the positive amount of money in the chosen gamble. If they did not want to play the gamble in the pay-off determining choice, they neither lost nor gained anything. Beliefs regarding the composition of the ambiguous bag and answers to the cognitive reflection task were not incentivized.

Results

Parameters for risk and ambiguity

Based on our participants' switching point, we defined their certainty equivalents (CE) and these parameters served as our dependent variables for risk and ambiguity. In contrast to Sutter et al. (2013) we did not remove participants who switched more than once. In this situation, we took the midpoint of several switching points in case participants had switched more than once from the gamble to the sure pay-off. CE_r and CE_a denote the certainty equivalents of the risky prospect respectively the ambiguous prospect. The parameter r captures individual's degree of risk taking.

$$r = 1 - CE_R/5$$

A value of r larger (smaller) than 0.5 indicates risk averse (risk seeking) behavior. A score of 0.5 means risk neural behavior. Individual ambiguity preferences are estimated as follows:

$$a = (CE_R - CE_A)/(CE_R + CE_A)$$

The difference between CE_r and CE_a is divided by the absolute level of the CE of risk and ambiguity in order to control for the fact that similar differences in CE will weigh more heavily for a risk averse participant than a risk neutral or risk seeking participant. This parameter a ranges from -1 (extreme ambiguity seeking) to 1 (extreme ambiguity aversion). A score of 0 indicates ambiguity neutrality (Wakker, 2010).

Summary statistics

On average, our experimental population was risk neutral (mean r value of 0.504, not significantly different from 0.5: $t(171)=0.401$,

p=0.345), but ambiguity averse (mean a value of 0.036, significantly higher than 0: $t(171)$=3.714, p<0.001). See Table 10 for an overview of the descriptive statistics of all our experimental variables.

The summary statistics from Table 10 demonstrate that participants were both significantly loss averse and prudent (the score for loss aversion was significantly different from 3, respectively different from a score of 2.5 for prudence, t-test, p<0.05). On average, adolescents' beliefs were in line with the ambiguity neutral probability, as they estimated 10.26 winning colored ping-pong balls in the ambiguous bag, not significantly different from 10. There were notable gender differences however. Girls, on average, expected an amount of 10.76 winning colored ping-pong balls in this bag, whereas boys, on average, thought there were 9.80 winning colored ping-pong balls in this bag (Mann-Whitney, z=-2.128, p<0.05). Surprisingly, girls did not differ in their ambiguity preferences compared to boys, and if anything they were more ambiguity averse (mean a value of 0.034 for boys and mean a value of 0.039 for girls). Finally, risk preferences did not significantly differ between boys and girls.

Table 10: Descriptive statistics

Variables	Observations	Mean	Std. dev.	Min	Max
Ambiguity	172	0.036	0.128	-0.84	0.36
Risk	172	0.504	0.124	0.025	0.95
Loss aversion	172	3.884	0.871	0	6
Prudence	172	3.843	1.317	0	5
Beliefs	172	10.262	3.130	2	16
CRT	172	1.977	0.979	0	3

Correlations

Table 11 provides a correlation matrix between our experimental variables and the school data. Risk and ambiguity were negatively correlated. Negative correlations between risk and ambiguity have been reported before (Akay et al., 2012; Cubitt et al., 2012; Sutter et al., 2013), though less frequently than positive relationships (Trautmann and van de Kuilen, 2013).

Furthermore, Table 11 shows a high correlation between the different measures that capture degrees of intelligence and/or cognitive abilities; the overall score for intelligence, the subcomponents of verbal, numerical and abstract reasoning, the scores on the CRT and pupil's mathematics grade were all positively correlated. Also, we found that prudence was positively correlated with overall intelligence, and specifically with the verbal intelligence subcomponent.

In line with our hypothesis, we found that risk preferences negatively correlated with participants' self-confidence; the more risk averse they were, the less positively they perceived their self-confidence (Figure 22). We did not find a relationship between ambiguity and self-confidence. Loss aversion neither played a role in adolescents' scores on self-confidence.

Multivariate analyses

Table 12 shows the results of a multivariate analysis to test the robustness of the bivariate correlations between our experimental variables and the demographic data. We found that risk and ambiguity remained negatively correlated in a multivariate analysis. Also, our non-parametric finding between gender and beliefs remained the same: girls had significantly higher beliefs regarding the amount of winning colored ping-pong balls in the ambiguous bag. Intelligence (participants' total score on general intelligence) was still a positive predictor of prudence after controlling for other demographics.

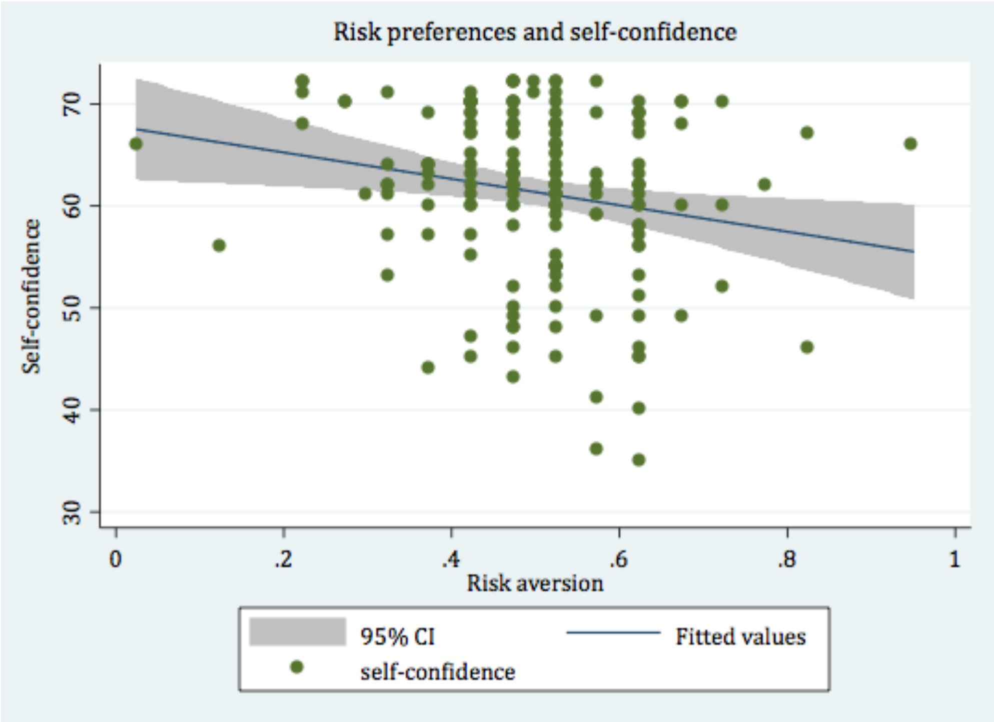
Finally, we analyzed the relationship between risk and self-confidence by looking at the subcomponents of social skills, confidence in exam-taking, and ability to express oneself in social situations. Risk aversion remained a significant predictor of the overall score for self-confidence (Table 13, models 1 and 2). Specifically, the more risk averse participants were, the more negatively they rated their social skills (Table 13, models 3 and 4).

Table 11: Correlation matrix

	Ambiguity	Risk	Prudence	Loss aversion	Beliefs	CRT	Intelligence	Verbal	Numerical	Abstract	Mathe-matics	Self-confidence	Well being	Motivation
Ambiguity	1													
Risk	-0.268***	1												
Prudence	0.122	0.016	1											
Loss aversion	0.112	0.144*	0.126*	1										
Beliefs	-0.096	-0.048	0.026	-0.105	1									
CRT	-0.115	0.108	0.056	-0.092	0.055	1								
Intelligence	0.001	-0.109	0.149**	-0.047	-0.005	0.355***	1							
Verbal	-0.014	0.032	0.150**	0.018	-0.031	0.192**	0.491***	1						
Numerical	0.015	-0.107	0.112	0.020	0.019	0.313***	0.797***	0.097	1					
Abstract	0.003	-0.095	0.112	-0.139*	-0.042	0.218***	0.714***	0.144*	0.342***	1				
Mathematics	-0.097	-0.75	0.069	0.009	0.018	0.254***	0.377***	0.209***	0.334***	0.214***	1			
Self-confidence	-0.010	-0.196***	0.007	-0.028	0.057	-0.006	0.164**	0.038	0.091	0.205***	0.035	1		
Well being	0.035	-0.115	0.010	0.030	0.037	-0.071	0.143*	-0.032	0.129*	0.137*	0.176**	0.143**	1	
Motivation	-0.024	-0.083	-0.021	0.033	0.090	0.019	0.112	-0.011	0.134*	0.083	0.295***	0.205***	0.611***	1

***, **, * significant at the 0.01, 0.05, 0.1 level, respectively

Figure 22: Participants' risk preferences and self-confidence



Finally, we performed some robustness analyses. As expected, we found that ambiguity aversion was influenced by the order in which participants made choices between the risky and ambiguous choice formats. In line with the comparative ignorance hypothesis (Fox and Tversky, 1995), the parameter for ambiguity aversion increased by 0.15 when participants had first made choices regarding the risky prospects, as compared to making the ambiguous choices first. Also, we found that 11 percent of our participants switched more than once from the gamble to the sure option in either the risky or ambiguous prospect. We created two dummy variables that indicate the order of playing the risky and ambiguous prospects, and whether a participant switched more than once. Our main results in this paper remain qualitatively valid when we analyzed the models in Table 12 and 13 with these dummy variables.

Table 12: Regression analyses

	Dependent variables:									
Independent variables:	**Ambiguity**		**Risk**		**Beliefs**		**Prudence**		**Loss aversion**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ambiguity				-0.267***		-2.198		1.282		0.935*
				(0.100)		(1.982)		(0.929)		(0.436)
Risk		-0.293*				-2.017		0.587		1.099**
		(0.156)				(2.203)		(0.759)		(0.581)
Beliefs		-0.003		-0.003				0.130		-0.032
		(0.003)		(0.003)				(0.031)		(0.022)
Prudence		0.012*		0.005		0.076				0.077*
		(0.007)		(0.006)		(0.180)				(0.043)
Loss aversion		0.020**		0.022**		-0.438		0.186*		
		(0.010)		(0.011)		(0.282)		(0.105)		
Age	0.000	0.000	-0.000	-0.000	-0.001	-0.001	0.000	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Intelligence	0.000	-0.000	-0.001*	-0.001*	0.000	-0.002	0.015*	0.015*	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.020)	(0.020)	(0.008)	(0.008)	(0.006)	(0.006)
Mathematics grade	0.001	-0.001	-0.007	-0.007	-0.027	-0.028	-0.006	-0.007	0.022	0.028
	(0.007)	(0.007)	(0.008)	(0.008)	(0.193)	(0.193)	(0.102)	(0.099)	(0.068)	(0.064)
Cognitive reflection task	-0.019*	-0.010	0.024**	0.021**	0.362	0.341	0.053	0.068	-0.054	-0.055
	(0.011)	(0.010)	(0.011)	(0.010)	(0.297)	(0.316)	(0.108)	(0.114)	(0.059)	(0.059)
Girls	-0.002	-0.005	-0.000	-0.001	1.098**	1.091**	0.455**	0.429*	0.074	0.075
	(0.020)	(0.021)	(0.019)	(0.017)	(0.498)	(0.506)	(0.219)	(0.221)	(0.134)	(0.129)
Constant	-0.082	0.043	0.785	0.654	12.629	16.188	1.670	-0.022	6.282	5.766
	(0.126)	(0.176)	(0.131)	(0.162)	(2.902)	(3.430)	(1.370)	(1.410)	(1.079)	(1.307)
Observations	172	172	172	172	172	172	172	172	172	172
F-test	F(5,166)=0.94	F(9,162)=2.31	F(5,166)=2.15	F(9,162)=2.90	F(5,166)=1.45	F(9,162)=1.56	F(5,166)=1.86	F(9,162)=2.08	F(5,166)=3.01	F(9,162)=3.16
Prob > F	0.456	0.018	0.062	0.003	0.201	0.130	0.104	0.034	0.013	0.001
R-squared	0.021	0.127	0.053	0.146	0.042	0.070	0.050	0.084	0.068	0.135

****,**,* significant at the 0.01, 0.05, 0.1 level respectively. Heteroskedasticity-corrected (robust) standard errors reported in parentheses.*

Table 13: Regression analyses

Independent variables:	Self image (1)	Self image (2)	Social status (3)	Social status (4)	Confidence exams (5)	Confidence exams (6)	Social expressions (7)	Social expressions (8)
	Dependent variables:							
Ambiguity	-4.266 (5.329)	-4.899 (4.889)	-3.569 (2.344)	-3.865* (2.206)	0.787 (1.844)	0.817 (1.763)	-1.484 (2.362)	-1.851 (2.287)
Risk	-14.142*** (5.106)	-11.733** (4.858)	-6.879*** (2.015)	-6.257*** (1.986)	-3.686 (2.472)	-3.168 (2.424)	-3.577 (2.295)	-2.308 (2.136)
Beliefs	0.109 (0.219)	0.203 (0.219)	0.040 (0.092)	0.083 (0.093)	-0.047 (0.095)	-0.003 (0.094)	0.116 (0.083)	0.123 (0.083)
Prudence	0.097 (0.520)	-0.062 (0.509)	0.145 (0.247)	0.125 (0.239)	0.058 (0.223)	0.021 (0.237)	-0.105 (0.228)	-0.208 (0.229)
Loss aversion	0.122 (0.619)	0.604 (0.635)	0.202 (0.277)	0.399 (0.312)	0.050 (0.333)	0.251 (0.310)	-0.130 (0.288)	-0.046 (0.307)
Age		0.003** (0.001)		0.001* (0.001)		0.000 (0.000)		0.001* (0.001)
Intelligence		0.080 (0.049)		0.014 (0.023)		0.031 (0.019)		0.035* (0.019)
Cognitive reflection task		-0.667 (0.720)		-0.199 (0.329)		0.049 (0.299)		-0.517* (0.292)
Girls		-0.776 (1.277)		-0.650 (0.583)		-1.013* (0.574)		0.887 (0.554)
Constant	66.631 (4.588)	39.205 (10.076)	22.138 (1.961)	13.017 (4.511)	22.253 (1.953)	13.475 (4.455)		12.713 (4.313)
Observations	172	172	172	172	172	172	172	172
F-test	F(5,166)= 1.61	F(5,166)= 2.03	F(5,166)= 2.53	F(9,162)= 2.13	F(5,166)= 0.76	F(9,162)= 2.00	F(5,166)= 1.28	F(9,162)= 2.38
Prob > F	0.160	0.039	0.031	0.030	0.583	0.043	0.276	0.015
R-squared	0.045	0.099	0.053	0.087	0.021	0.081	0.035	0.099

****,**,* significant at the 0.01, 0.05, 0.1 level respectively.*
Heteroskedasticity-corrected (robust) standard errors reported in parentheses.

Discussion

In this study we were interested in expanding current knowledge regarding preferences for uncertainty by examining the economic constructs of risk and ambiguity in a sample of adolescents, and how these related to social uncertainty, in particular self-confidence in one's social standing. Additionally, we explored how a previously understudied aspect of risk, namely prudence, was represented in this age-group.

Adolescence is a time period characterized by the importance of peer-to-peer contacts and peer evaluation (Somerville, 2013), while at the same time, these relationships are in a constant state of flux (Wang et al., 2009). Therefore, we hypothesized that adolescents who were more risk and ambiguity averse would also express more uncertainty regarding their social standing at their high school. We found a positive relationship between risk aversion and self-confidence in adolescents. When we investigated the subcomponents of self-confidence, this effect appeared primarily driven by self-reported ratings of social skills. In other words, adolescents who were more risk averse were more uncertain regarding their social skills. In a further multivariate analysis this relationship remained qualitatively valid when controlling for other elicited experimental variables and demographic characteristics such as age, gender, and intelligence. Additionally, these results did not change when we introduced two dummy variables, which characterized those subjects who were impacted by the order of playing the risky and ambiguous prospects and also those who switched multiple times between the prospects and the sure option in the risky and/or ambiguous gamble.

We did not find a relationship between ambiguity and self-confidence. We suspect that adolescents are well aware of their social standing amongst their peers, that is, if peer contacts do not run smoothly, peer rejection often follows (Wang et al., 2009). This direct feedback offers continuous information about adolescents' social environment. In other words, adolescents are able to assess their social standing and how it evolves over time as a result of peer bonding and peer rejection. Continuous information on social standing therefore may correspond better to risk as a type of uncertainty. We suggest that this might be a potential explanation for the demonstrated relationship between risk and social standing, but the absence of one between ambiguity and social standing. Similarly, Sutter et al. (2013) also found that the relationship between ambiguity and real-life health choices was quite weak, at best.

It is also interesting to review the basic findings from our adolescent pool, as experiments with adolescents are still relatively rare (von Gaudecker et al., 2011). We also did not find an indication of risk averse behavior in adolescents (Harbaugh et al., 2007; Levin et al., 2002; Steinberg, 2004). However, we did find evidence of ambiguity averse preferences. Interestingly, Tymula et al. (2012) found the exact opposite pattern, that is, risk averse and ambiguity tolerant behavior in adolescents. As there is evidence showing that individual preferences for risk and ambiguity are highly dependent on the specific elicitation method (Charness et al., 2013), we believe this might be a potential explanation for the differences in results. Upon examining the elicitation methods of Tymula et al. (2012), it is evident that their experimental procedures were substantially different than ours. In their setup, ambiguity was operationalized as a weak form by offering lotteries whereby only part of the unknown bag was revealed, which is in contrast to our ambiguous setup where the unknown bag was completely unknown. Their procedure is more in line with a compound lottery and it is known that this is perceived differently than complete ambiguity (Halevy, 2007). On the other hand, we used the same procedure to elicit risk and ambiguity as Sutter et al. (2013), with our results aligning in that we both identify ambiguity averse preferences in adolescents. That elicitation methods might be a reason for the aforementioned differences in results becomes even more plausible when we compare our correlation between risk and ambiguity preferences to previous reported correlations. We found risk and ambiguity preferences to be negatively correlated. As most studies report positive relationships between risk and ambiguity (Trautmann and van de Kuilen, 2013), it is interesting to note that those studies that employed the same elicitation procedure as ours also reported a negative correlation between risk and ambiguity (Sutter et al., 2013; Akay et al., 2012; Cubitt et al., 2012). A final note regarding differences between these methods is that the elicitation technique used in Tymula et al. (2012) provides a convenient way to model increasing uncertainty, but it does not capture true ambiguity in the sense of unknown probabilities, yet it assumes that people form second-order expectations concerning real-life decisions. On the other hand, Ellsberg urn experiments, which we used in this study, have been most frequently used to elicit ambiguity aversion because they are transparent, easily implemented and truly capture preferences regarding unknown probabilities (Trautmann and van de Kuilen, 2013, p. 94).

Although it is reassuring that we found similar results as other experimental studies on risk and ambiguity which employed similar elicitation techniques, the ultimate goal is to identify adolescents' preferences for risk and ambiguity. The Ellsberg paradigm, which we used in this experiment, is a very standard elicitation technique to measure individuals' ambiguity preferences and it has been used in many experimental studies with non-adolescent samples (Trautmann and van de Kuilen, 2013). Majority of these studies reported risk and ambiguity aversion (Trautmann and van de Kuilen, 2013). Based on our results, we can conclude that adolescents dislike ambiguity, as do adults. On the other hand, adolescents' CEs for the risky prospect were in accordance with the expected value of the risky prospect, and thus they cannot be characterized as risk averse, which is commonly found in adults.

Although we did not measure risk perception in this study, it has been shown that risk preferences and risk perception are correlated (Weber et al., 2002; 2006). Although most real-life events cannot be described in terms of objective probabilities and are thus rather ambiguous than risky (Post et al., 2008), it seems that adolescents, especially those who report participating in potential harmful activities, report that they are better informed as to associated 'risks' (Cohn et al., 1995). Moreover, they are more likely to minimize the perceived risks of potential harmful activities, like for instance getting drunk when consuming alcoholic beverages (Cohn et al., 1995). The combined effect of adolescents' neutral attitude towards risks and their tendency to minimize risks related to harmful activities could potentially explain why adolesents engage more often in risky activities compared to other age-groups. In order to verify this intuition, in future studies we propose to directly relate the relationship between risk perception and risk preferences on adolescents' behavior in real-life.

In contrast to risk perception we did measure adolescents' perception regarding the underlying likelihood in the ambiguous prospect. Namely, we explicitly asked participants to report their beliefs regarding the composition of the ambiguous bag. An interesting finding in our experimental sample was the gender difference in beliefs regarding the composition of the ambiguous bag. We found that girls, compared to boys, expected one more ping-pong ball of their selected color in the ambiguous bag. It was rather surprising that girls did not act on their more positive beliefs by expressing more willingness to gamble in the ambiguous lottery. Namely, we could not identify any gender differences in ambiguity aversion. Future research could investigate if confidence in one's stated beliefs is a possible explanation why girls were not willing to express more ambiguity seeking behavior, as compared to boys, despite substantial higher beliefs regarding the ambiguous prospect. Further research could also look into the relationship between perceived likelihood and perceived risk in adolescents. If adolescents indeed minimize perceived risks, yet overweight perceived likelihoods, the latter is a common finding in adults (Abdellaoui et al., 2011), this could potentially explain the negative correlation between risk and ambiguity preferences.

Our results also highlight that adolescents are sensitive to a particular moderator of ambiguity, known as the comparative ignorance effect (Fox and Tversky, 1995), whereby ambiguity aversion is increased when participants experience ambiguity after they have been first exposed to risk. Research suggests that the uncertain aspect of the ambiguous prospect is particularly discomforting as it can be easily compared to the clear information structure of the risky prospect, which evidently occurs when participants first indicate their choices for the risky prospect before making choices in the ambiguous prospect (Rubaltelli et al., 2010). Based on our findings we can conclude that, as with adults, adolescents are more prone to ambiguity aversion when they have the possibility to evaluate clear and vague prospects jointly. Related to this moderator, Fox and Tversky (1995) also showed that knowledge and specific expertise can diminish the distinction between clear and vague choice events, and can flip individual preferences from ambiguity aversion to ambiguity seeking and vice versa. Namely, if people (think they) possess knowledge regarding an ambiguous prospect, this prospect does not seem vague to them anymore, which will not necessarily lead to ambiguity aversion in this case. It would be worthwhile to test how perceived expertise on more real-life ambiguous events guides adolescents in their decision-making under uncertainty.

In our experiment we also tested attitudes of prudence in adolescents. To the best of our knowledge, this is the first study examining this higher-order risk attitude in adolescents. For a prudent individual, the expected marginal utility of saving increases as background risk increases. In our experimental task on prudence, this behavior is identified when participants prefer to disaggregate harms of accepting a smaller monetary outcome and a zero-mean risky lottery (Rothschild and Stiglitz, 1970). Our experimental population was, on average, significantly prudent. Noussair et al. (2013) also showed that their population of undergraduate students expressed prudence.

In line with Nousair et al. (2013), we also found that prudence and intelligence were positively correlated, but intelligence did not correlate with risk or ambiguity aversion. Our findings support the view that prudence is particularly pervasive among people with high cognitive ability and education (Noussair et al., 2013, p. 345).

Theoretical predictions (Kimball, 1990) and the empirical result of Noussair et al. (2013) stress the importance of prudence for precautionary saving behavior. Namely, in the presence of future income risk, agents who are prudent save more. As Sutter et al. (2013) found a positive correlation between intelligence and saving behavior in their adolescent population, it might well be that prudence is one of the underlying explanatory drivers. Future studies could focus on directly relating a prudent attitude of adolescents to their saving behavior.

It is also interesting to consider the correlation between risk aversion and prudence. Experimental studies on prudence with non-adolescent samples report a positive correlation between risk aversion and prudence (Ebert and Wiesen, 2010; Noussair et al., 2013). We did not find a correlation between risk aversion and prudence in adolescents. Although Noussair et al. (2013) did not address this in their main text, their correlation matrix illustrated a non-significant correlation between risk aversion and prudence in their student sample, as opposed to a significant positive correlation between risk aversion and prudence in their representative panel sample of adults. Subsequently, when they excluded risk neutral individuals from their sample, who should in theory be indifferent between prudent and imprudent gambles, they still found evidence of prudence in the remaining sample. These findings support our result that adolescents can be risk neutral, yet averse to higher-order risk attitudes.

Aversion to higher-order risk attitudes could affect adolescents in their decision-making as they will soon either experience a transition from high school to college or from high school to the workforce. Those adolescents who will pursue an educational trajectory have to rely more on student loans as financial benefits for students are cut down due to economic turmoil in many countries (Chapter 5). As already explained before, a prudent individual has a tendency to save when background risk increases, instead of obtaining a student loan. Moreover, it is rather worrisome that prudence is especially prevalent amongst those who have the highest cognitive ability and will therefore probably pursue a longer than average educational trajectory. A follow-up study on our experiment from Chapter 5 could test if prudence is prevalent in those students who borrow least. On the other hand, those adolescents who will enter the workforce soon and which show indication of prudent behavior might select into jobs with low income risk (Browning and Lusardi, 1996), yet perhaps less future career prospects. A follow-up study could explicitly relate adolescents' attitude towards prudence and their preferred job options in the future.

All of the findings we reported in this paper can be related to a larger discussion of whether experimentally elicited preferences for uncertainty relate to real-life decision-making under uncertainty. Some researchers argue for eliciting domain specific risk preferences (Weber et al., 2002), whereas others state that risk and ambiguity preferences can be captured by one general measurement (Dohmen et al., 2011; Vieider et al., 2014; Lauriola et al., 2007), thus suggesting that risk and ambiguity attitudes are somewhat stable across contexts. Our results show that risk preferences elicited via a standard lottery setup correlate with adolescents' self-confidence regarding their social skills at their high school. This result shows that risk, elicited via a lottery, captures an aspect of risk in another, more social, decision domain. At the same time, individual lottery risk preferences did not explain adolescents' variation in confidence ratings of taking exams. As there are relatively few studies that investigate the relationship between experimentally elicited variables and real-life decision variables, more research is needed to follow-up on the specificity when it comes to relating risk and ambiguity to real-life decision-making under uncertainty, especially in the population of adolescents.

Throughout the discussion we have outlined several variables that should be taken into account if we aim to provide a good characterization of adolescents' decision-making under uncertainty. A unifying experiment that looks at the interaction between risk perception, risk preferences, beliefs, confidence in beliefs, ambiguity preferences and prudence could specifically pinpoint why adolescents are at the same time risk neutral, yet ambiguity averse and prudent. This would also aid in designing better policies to protect adolescents from engaging in harmful risky activities and/or saving too much when background risk increases.

Apart from providing useful directions for follow-up studies, our results already demonstrate that preferences for risk, elicited by a standard lottery, capture a meaningful aspect of social uncertainty in adolescents. Adolescents' confidence regarding their social standing is an important aspect of their mental health. Understanding social uncertainty in adolescents as a general aversion to risk, amongst other causes, could help pedagogues to identify and design better training to help those adolescents who are struggling with their social standing.

Chapter 7

Discussion and conclusion

Summary

The central theme of this thesis is DMUU. We aimed to understand how sources and types of uncertainty affect individual's decision-making and their external validity. We explored this topic with several research methodologies. This enabled us to investigate why sources and types of uncertainty play a role in the mind of a decision-maker and how this affects real-life decision-making.

In Chapter 2 we studied sources of risk. In economics, preferences for risk and ambiguity are predominantly elicited by lottery setups (Charness et al., 2010; Dohmen et al., 2011; Lauriola et al., 2007). In real life, however, uncertainty often stems from the actions of other decision-makers, referred to as strategic uncertainty (Houser et al., 2010). Hence, there is a difference between the sources of uncertainty regarding typical preference elicitations and situations of strategic uncertainty. The distinction between these sources of uncertainty was the main topic of Chapter 2. We focussed on the Trust Game as previous research that related individual preferences for risk, elicited via a lottery, to individual trust, as observed in the Trust Game, found mixed results (Eckel and Wilson, 2004; Ashraf et al., 2006; Ben-Ner and Halldorsson, 2010; Houser et al., 2010; and Etang et al., 2011). In Chapter 2 we shed some light on the reason why these results might be so mixed. We developed a risky version of the Trust Game (RTG), which underlying source of uncertainty, namely the risk of betrayal by a Trustee, was aligned with strategic uncertainty in the Trust Game. Indeed, our results showed that behavior in the RTG influenced the amount of trust a Trustor displayed in the Trust Game. On the other hand, our participants' risk preferences, elicited via a lottery, did not correlate with their decision to trust in the Trust Game. This paper illustrated that a lottery measurement of risk (Holt and Laury, 2002) does not capture the risk a decision-maker faces in a strategic context such as the Trust Game.

In Chapter 3 we extended our paradigm of the RTG to include ambiguity. We were able to investigate a fourfold pattern of types and sources of uncertainty. Prior to the decision-making phase we elicited individuals' beliefs concerning receiver's reciprocity in the Trust Game. We used these individual beliefs to create so-called belief-corresponding scenarios whereby participants faced a lottery setup with an equal underlying likelihood. This study was conducted in an MRI scanner. We specifically investigated the neural correlates of individuals' ambiguity preferences in both lottery and social domains. We found a main effect of ambiguity aversion. Although ambiguity aversion was, on average, also prevelant when the underlying source of uncertainty stemmed from another decision-maker and we did not find significant differences in responses between the risky and ambiguous lottery, this interaction was not significant. Likewise, we found similar brain areas actively involved for both sources of uncertainty. We found substantial individual differences in social ambiguity preferences when taking individual differences in beliefs into account. These individual differences have a neural basis, as activation in the IFG correlates with the degree of social ambiguity aversion. We did not find neural correlates of individual differences related to lottery ambiguity preferences. The IFG is involved in establishing accurate perceptual judgments about other peoples' actions (Pobric et al., 2006). Overall, these findings suggest that the IFG is involved when decision-makers are deciding under uncertainty, and specifically when the uncertainty is resolved by another person.

In economics we assume that DMUU is guided by individual beliefs (Savage, 1954). In our behavioral setup in Chapter 3 we indeed found that individuals invested most of their tokens when they expected a higher rate of reciprocation amongst Trustees in the Trust Game. This notion that individuals' beliefs are powerful enough to explain decision-making is not so deeply rooted in the field of neuroscience (Glimcher and Rustichini, 2004). In Chapter 4 we aimed to show that individuals' beliefs directly affect neural mechanisms of anticipated reward. Anticipatory reward is a well-studied topic in neuroeconomics (Fiorillo et al., 2003; Schultz et al., 1997; Schultz et al., 1998; Schultz, 2010). The monetary incentive delay task by Knutson et al. (2000) is a common approach to experimentally studying anticipated reward modalities in humans. In this task participants have to perform some task (e.g. a button press task in which they need to hit a button within a certain time-limit) in order to receive rewards or avoid losses. Importantly, prior to this task, participants have learned to associate, via performing the button press task, which abstract cues will lead to gains and losses. In this Chapter we used the neural data of the second part of the same fMRI experiment conducted in the previous chapter. In this second part of the experiment, participants experienced the outcomes of their choices while still lying in the MRI scanner. Here, we investigated whether decision-makers' beliefs about the outcomes of their choices can also act as a cue for reward anticipation. As the neural correlates of anticipated rewards are very robustly identified in the ventral striatum (Knutson et al., 2001; Knutson and Greer, 2008), we identified a similar expected reward signal in the striatum when participants were awaiting their outcomes in our experimental setup. This expected reward signal stems from participants' own invested choices as modulated by their beliefs. These results stress that belief-mediated anticipatory rewards are just as powerful in activating an expected reward signal as when humans learn to associate abstract cues with rewards in a task like the monetary incentive delay task.

In Chapters 5 and 6 we extended sources and types of uncertainty beyond the laboratory. Although risk and ambiguity preferences are well-researched behavioral constructs in the artificial environment of the laboratory, few empirical translations, especially for ambiguity, have been undertaken (Trautmann and van de Kuilen, 2013).

In Chapter 5 we tested the external validity of risk and ambiguity preferences by relating students' ambiguity attitudes to their borrowing behavior. Although the relationship between risk and students' borrowing behavior had been identified (Oosterbeek and van den Broek, 2009), we considered ambiguity as an important type of uncertainty within this real-life decision context. We hypothesized that students' aversion to borrowing may be primarily driven by their aversion to ambiguity regarding the repayment of their loans. Indeed, we found a negative relation between students' ambiguity aversion and the amount they borrowed. We could not identify a relationship between students' risk preferences and their borrowing behavior.

In Chapter 6 we conducted a field study with adolescents during regular school hours at their high school. We measured adolescents' risk and ambiguity preferences and related these to demographic data and a collection of psychological and school performance measures, which were directly provided by the high school. We were mostly interested in testing the relationship between risk and ambiguity, as measured by standard economic experimental tasks, and an important aspect of mental health, namely adolescents' self-confidence levels. Self-confidence is shaped by self-belief regarding own capabilities and social standing. This last feature is especially important during adolescence, as adolescents are much concerned about peer-to-peer evaluation. Although adolescents spend a lot of time with their peers, either in real life or in the digital world (Larson, 2001; Lenhart, Ling, Campbell, & Purcell, 2010), these relationships are not very stable. Friends come and go and adolescents will, more frequently compared to other age groups, experience peer rejection (Wang, Iannotti and Nansel, 2009). We studied whether less risk and ambiguity averse adolescents flourish more in their confidence regarding their social relationships. We indeed found that risk aversion in adolescents correlate with self-confidence. In particular, risk aversion affected the way adolescents perceived their own social skills at their high school.

Policy relevance

As DMUU is a viable part of our daily lives, our research into sources and types of uncertainty has the potential to help individual decision-makers and to inform policy makers to better design public policy (Farber, 2011).

Firstly, this thesis showed that in strategic uncertainty settings, it is important to consider the source of uncertainty decision-makers face. In real-life one can think of many economic relationships where people need to interact with others in order to cooperate, trade or invest. Many of these interactions occur with others across the world, which taps more into ambiguity as type of uncertainty. Companies and governments should be aware that social ambiguity aversion is a prominent feature of individuals' decision-making. This should be particularly valuable to those in positions of power, as there is evidence that a society in which trust in other people is low, negatively influences economic performance (Knack and Keefer, 1997).

The personal example I started with in the Introduction of this thesis was an illustration of strategic uncertainty. As I had to transfer a substantial amount of money via Western Union to somebody I had never met, it was difficult to assess the odds of being scammed. Fraud occus frequently via a money agency like Western Union. With the phrase 'fraudsters gain your trust and then steal your money', Western Union aims to create fraud awareness on their website. Instead of trying to establish awareness to detect potential fraud, the uncertainty in a succesfull outroll of their transactions would greatly be reduced if Western Union offered a proper and thorough background check on the end-receiver. As this is not an exercise in comparing which companies or governments perform better, I do want to mention a counter example of the company Airbnb, which I recently learned takes great care in reducing strategic uncertainty for both renters and landlords. This company performs detailed background checks before allowing individuals to use their services, and in contrast to Western Union, they have a clear refund policy if the transaction does not go through properly. Via these policies, the uncertainty concerning interacting economic partners around the globe substantially decreases, and this might be a way to facilitate interactions characterized by strategic uncertainty. A last note on sources of uncertainty is that public policy makers who wish to identify if individuals are particularly averse to social sources of uncertainty, should take into account that preferences for risk and ambiguity cannot be solely captured by lottery elicitations measures, but has to be measured via an elicitation procedure that aligns sources of uncertainty (see Chapter 2 and 6).

Moreover, policy makers might also want to consider both types of uncertainty. Individuals mostly face decision problems that are characterized as ambiguity as most choice events cannot be defined by exact probabilities. More research is needed that aims to test the external validity of <u>both</u> types of uncertainty in the field. For instance, the relationship we addressed between ambiguity attitudes and students' borrowing behavior led us to formulate explicit policy recommendations. We proposed to introduce a guarantee that the government will act as a last resort in case of loan default and more stable future interest rates to reduce ambiguity.

Limitations

This thesis naturally has some limitations, which at the same time offer opportunities for future research (see below). The limitations that we want to make explicit concern the low statistical power in fMRI experiments, our tailor-made design structure based on participants' beliefs in Chapters 3 and 4, and finally the survey measures we used as real-life decision-making indicators in Chapters 5 and 6.

Neuroimaging experiments are more expensive than conventional behavioral laboratory experiments due to the high operations costs of the MRI scanner. Therefore, fMRI experiments have always been characterized by relatively small sample sizes (Huettel et al., 2009). Recently, the debate on sample sizes in neuroscientific research has become more prominent due to an influential article (Button et al., 2013), which posed that low sample sizes in neuroscience cause low statistical power. The fMRI experiments we completed in this thesis (see Chapter 3 and 4) were conducted with a number of participants that adheres to convential sample sizes in neuroscience research (Huettel et al., 2009). Yet, in light of this recent debate, and as our research points towards individual differences in ambiguity preferences, a larger sample size is an important point to take into consideration for future fMRI studies.

An important variable throughout our thesis has been the role of individuals' beliefs on DMUU (see Chapter 2 and 3) and anticipated rewards (see Chapter 4). As we aimed to examine sources and types of uncertainty in one experimental design, we had to control for individual variation in beliefs. In contrast to beliefs in social contexts, subjective probabilities can be easily manipulated in a lottery context. We aligned elicited beliefs in the ATG to an equal underlying likelihood to draw a winning-colored marble in the ALOT and corresponding objective probabilities in the RTG and RLOT (see Figure 1, Chapter 3). Although this design enabled us to study neural effects of sources and types of uncertainty without individual beliefs as confounds, it is important to bear in mind the interpretation of our result. For one, we cannot compare individual differences in lottery ambiguity preferences as they solely faced a likelihood, which stemmed from their beliefs in the ATG. Also, our procedure of aligning beliefs from the social context to the lottery source produced a difference in the amount of information given between both sources. A consequence of this approach is that participants in the ALOT did not actively have to form a prior belief and therefore our interpretation between the contextual differences in ambiguity preferences and belief-mediated anticipated rewards should be interpreted with some caution. A small robustness-check we carried out to see if participants might experience the uncertainty across our social and non-social sources of uncertainty differently was to compare the standard deviation of their investment chocies across contexts. Namely, if participants might feel that the ATG is more uncertain compared to the ALOT, due to differences in information received, we reasoned that they would vary more in their investment choices in the ATG. We did not find any evidence suggesting this was the case. A final note on beliefs is that we did not take confidence in beliefs into consideration. For example, if participants expressed the same belief, yet they differ in their confidence concerning their stated belief, this might have an effect on their behavior. In subsequent research, as also outlined below, we want to understand how beliefs are shaped; confidence is one variable to take into consideration as well.

A final limitation we want to discuss are the survey measures we used as real-life indicators for decision-making in Chapters 5 and 6. Due to privacy reasons we could not obtain students' ambiguity borrowing behavior from the corresponding organization that lends students these loans. We have no reason to assume that students would lie about their borrowing behavior. We also took great care in reassuring them that these details kept private and were only considered for research purposes. In Chapter 6 the high school, at which we conducted our experiment, provided data on adolescents' scores on a set of psychological measures. From these measures we extracted our dependent variable, namely adolescents' scores on the concept of self-confidence. These scores came from validated tests, which were conducted at high school during participants' first school year. Nonetheless, if we would have had more time to conduct our experiment outside the class, which was now limited to 50 minutes, we would have validated these original scores with some other measures that proxy for self-confidence.

Future research

In this thesis we used several methodologies to understand how decision-makers react to sources and types of uncertainty and subsequently how this affects real-life decision-making. An outcome of this approach is that we could indentify behavioral and neural effects of individual differences in DMUU (see Chapter 3) and anticipated rewards (see Chapter 4) as a function of individual beliefs. It would be interesting to follow up on these outcomes by assessing why people have high or low priors concerning the reciprocity of others. Are these shaped over the course of one's life through personal experiences, or are they more biologically determined? Our results from Chapter 6 at least suggest that there are substantial differences in beliefs between girls and boys. Subsequently, another possible study could examine the extent to which individuals' social priors are adaptive and can be influenced. For instance, if a follow-up study would find that social priors in the context of DMUU are to some extent biologically determined, then hormonal interventions, similar to studies on oxytocin and trust (Kosfeld et al., 2005), could be a nice follow-up.

Another interesting avenue for future studies is how decision-makers update their beliefs based on the outcomes they experience. This would implicate a dynamic follow-up study on the design discussed in Chapter 4. Learning about ambiguous assets has been labeled a promising future direction in a recent meta-analysis on experimental ambiguity research (Trautmann and van de Kuilen, 2003). Yet, in the spirit of this thesis, we would propose to also take sources of uncertainty into consideration. Especially as we found in Chapter 4 that belief-mediated anticipated rewards are observed in the social context, but not in the lottery context. We suggested that this is due to the fact that social priors are probably stronger than priors established through mechanistic devices. Subsequently, future studies could examine dynamic learning setting in ambiguity whereby sources of uncertainty are taken into account as well.

Finally, in Chapters 5 and 6 we investigated the external validity of risk and ambiguity. Based on these results we proposed some policy recommendations. It would come full circle if follow-up studies could examine, if based on the interaction between types of uncertainty and real-life decision-making, these interventions prove to be successful in changing peoples' behavior. For instance, based on the literature on social norms, successful intervention studies have been undertaken, which successfully increased more environmental friendly behavior (Fairley et al., 2013). Likewise, intervention studies could be conducted to test if students will take out higher student loans if the government will act as a last resort in case of loan default and more stable future interest rates will be introduced.

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Appendix

1)
Appendix - Trust and risk revisited

You can find the instructions of our experiment below. Subsequently we explain the coding scheme of remaining incentivized auxiliary measures we did not discuss in the main paper. Finally we perform additional robustness analyses to show that our main results hold.

Instructions
Note: task 1 is the lottery ambiguity task, task 2 is the social preferences task, task 3 is the lottery risk task and finally task 4 is the Trust Game.

INTRODUCTION
You will now participate in an economic experiment. In this experiment, you will earn money depending on the decisions that you will make. For this reason, it is very important that you read these instructions carefully.

During the experiment, your income will be expressed in tokens. The total amount of tokens which you earn will be converted to Euro's at the end of the experiment; the following conversion rate applies:

1 token = € 0,50

You will be paid in cash at the end of the experiment. The payment will be made in privacy; no other participant will learn how much you earned.

Please note that you are not allowed to communicate with other participants during this experiment. Should you have any questions, please raise your hand and we will come to you to answer them. Note however that we do not answer questions of the type - 'what shall I do in the experiment' – this is your own choice. We, however, are happy to answer questions on how to use the computer to make decision, and to explain the details of the experiment instructions.

The experiment consists of five independent Tasks. At the beginning of each task, you will receive instructions.
You will make decisions in each of the Tasks, and will be paid based on your decisions, and possibly decisions of other subjects in the experiment.
At the end of the experiment, you will learn the outcome of each Task, as well as how many tokens you collected in the individual Tasks. The total amount earned in the experiment will be then paid to you, individually. No other experiment participant will learn how much you earned.

Task 1

This task consists of two parts. In EACH part, there are 20 rows. In each row, you are asked to choose between Option A and B. After the experiment, the computer will randomly pick one of the 20 rows of each part of the Task, and determine your earnings based on your decision in these rows.

If you choose option A in the selected row, you will receive the amount of tokens given at this row. If you choose option B, the computer will randomly pick one out of 10 balls. Each ball is either blue or yellow. If the color of the ball picked by the computer is yellow, your earning will be 5 tokens, otherwise 0 tokens.

There is only one difference between part 1 and part 2 of this task.

In part 1, THERE ARE 5 blue and 5 yellow balls, and the computer randomly picks one out of them.
In part 2, YOU WILL NOT learn from how many blue and yellow balls there are among the 10 balls, and any composition of the two colors of the balls is possible.

1) In this first part of the task, there are 10 balls**:** 5 yellow balls and 5 blue balls. Please indicate for each row if you prefer receiving the certain amount of tokens at that row, or you choose to draw a ball. If you choose to draw a ball, the computer will randomly select one out of the 5 blue and 5 yellow balls, and the color of the selected ball will determine your earnings. You will be asked to enter your decision at the computer screen.

	Option A	Option B
1	O I choose the certain amount of 0.25 tokens	O I choose to draw a ball
2	O I choose the certain amount of 0.50 tokens	O I choose to draw a ball
3	O I choose the certain amount of 0.75 tokens	O I choose to draw a ball
4	O I choose the certain amount of 1 tokens	O I choose to draw a ball
5	O I choose the certain amount of 1.25 tokens	O I choose to draw a ball
6	O I choose the certain amount of 1.50 tokens	O I choose to draw a ball
7	O I choose the certain amount of 1.75 tokens	O I choose to draw a ball
8	O I choose the certain amount of 2 tokens	O I choose to draw a ball
9	O I choose the certain amount of 2.25 tokens	O I choose to draw a ball
10	O I choose the certain amount of 2.50 tokens	O I choose to draw a ball
11	O I choose the certain amount of 2.75 tokens	O I choose to draw a ball
12	O I choose the certain amount of 3 tokens	O I choose to draw a ball
13	O I choose the certain amount of 3.25 tokens	O I choose to draw a ball
14	O I choose the certain amount of 3.50 tokens	O I choose to draw a ball
15	O I choose the certain amount of 3.75 tokens	O I choose to draw a ball
16	O I choose the certain amount of 4 tokens	O I choose to draw a ball
17	O I choose the certain amount of 4.25 tokens	O I choose to draw a ball
18	O I choose the certain amount of 4.50 tokens	O I choose to draw a ball
19	O I choose the certain amount of 4.75 tokens	O I choose to draw a ball
20	O I choose the certain amount of 5 tokens	O I choose to draw a ball

2) In this second part of the task, there are 10 balls: but you will not be informed how many of them are blue and how many are yellow. Please indicate for each row if you choose the certain amount at that row, or you choose to draw a ball. If you choose to draw a ball, the computer will randomly select one out ten balls of unknown color mix between yellow and blue balls, and the color of the selected ball will determine your earnings. You will be asked to enter your decision at the computer screen.

	Option A	Option B
1	O I choose the certain amount of 0.25 tokens	O I choose to draw a ball
2	O I choose the certain amount of 0.50 tokens	O I choose to draw a ball
3	O I choose the certain amount of 0.75 tokens	O I choose to draw a ball
4	O I choose the certain amount of 1 tokens	O I choose to draw a ball
5	O I choose the certain amount of 1.25 tokens	O I choose to draw a ball
6	O I choose the certain amount of 1.50 tokens	O I choose to draw a ball
7	O I choose the certain amount of 1.75 tokens	O I choose to draw a ball
8	O I choose the certain amount of 2 tokens	O I choose to draw a ball
9	O I choose the certain amount of 2.25 tokens	O I choose to draw a ball
10	O I choose the certain amount of 2.50 tokens	O I choose to draw a ball
11	O I choose the certain amount of 2.75 tokens	O I choose to draw a ball
12	O I choose the certain amount of 3 tokens	O I choose to draw a ball
13	O I choose the certain amount of 3.25 tokens	O I choose to draw a ball
14	O I choose the certain amount of 3.50 tokens	O I choose to draw a ball
15	O I choose the certain amount of 3.75 tokens	O I choose to draw a ball
16	O I choose the certain amount of 4 tokens	O I choose to draw a ball
17	O I choose the certain amount of 4.25 tokens	O I choose to draw a ball
18	O I choose the certain amount of 4.50 tokens	O I choose to draw a ball
19	O I choose the certain amount of 4.75 tokens	O I choose to draw a ball
20	O I choose the certain amount of 5 tokens	O I choose to draw a ball

You will be informed about the outcome of this task at the end of the experiment. Please raise your hand if you have any questions.

Task 2

In this task, you will be randomly matched to one another subject in this experiment. One of you two will be assigned at random the role of the SENDER in this task, and the other one is assigned the role of the RECEIVER.

You will learn whether you are SENDER or RECEIVER in this task, only at the end of the experiment. Therefore, you have to indicate your choice below for the case that you will be assigned the role of the SENDER.

In this task, you will face 24 situations. In each of them, you are asked to choose one out of two options. In case you will be assigned the role of the SENDER, the option that you choose could have monetary consequences for you and also for the other person, the RECEIVER.

In case you will be assigned the role of the RECEIVER, the choices made by the other subject, the SENDER, will determine your earnings.
At the end of the experiment, the computer will select one out of the 24 decision situations at random, and the chosen alternative of the SENDER in that situation will determine the earnings of the SENDER and the RECEIVER.
Let us now explain the options available in each of the 24 decision situations. For each option, two numbers will be displayed: the number of points you will receive yourself (positive or negative) when you choose this option, and the number of points (positive or negative) the other subject will receive when you choose this option. These situations are listed below. You will be asked to enter your decision at the computer screen.

	OPTION A		OPTION B	
	SENDER	RECEIVER	SENDER	RECEIVER
SITUATION1	3 tokens	0 tokens	2.90 tokens	-0.78 tokens
SITUATION2	2.90 tokens	-0.78 tokens	2.60 tokens	-1.50 tokens
SITUATION3	2.60 tokens	-1.50 tokens	2.12 tokens	-2.12 tokens
SITUATION4	2.12 tokens	-2.12 tokens	1.50 tokens	-2.6 tokens
SITUATION5	1.50 tokens	-2.60 tokens	0.78 tokens	-2.90 tokens
SITUATION6	0.78 tokens	-2.90 tokens	0 tokens	-3 tokens
SITUATION7	0 tokens	-3 tokens	-0.78 tokens	-2.90 tokens
SITUATION8	-0.78 tokens	-2.90 tokens	-1.5 tokens	-2.60 tokens
SITUATION9	-1.50 tokens	-2.6 tokens	-2.12 tokens	-2.12 tokens
SITUATION10	-2.12 tokens	-2.12 tokens	-2.6 tokens	-1.50 tokens
SITUATION11	-2.60 tokens	-1.50 tokens	-2.90 tokens	-0.78 tokens
SITUATION12	-2.90 tokens	-0.78 tokens	-3 tokens	0 tokens
SITUATION13	-3 tokens	0 tokens	-2.90 tokens	0.78 tokens
SITUATION14	-2.90 tokens	0.78 tokens	-2.6 tokens	1.50 tokens
SITUATION15	-2.60 tokens	1.50 tokens	-2.12 tokens	2.12 tokens
SITUATION16	-2.12 tokens	2.12 tokens	-1.50 tokens	2.6 tokens
SITUATION17	-1.50 tokens	2.60 tokens	-0.78 tokens	2.90 tokens
SITUATION18	-0.78 tokens	2.90 tokens	0 tokens	3 tokens
SITUATION19	0 tokens	3 tokens	0.78 tokens	2.90 tokens
SITUATION20	0.78 tokens	2.90 tokens	1.50 tokens	2.6 tokens
SITUATION21	1.50 tokens	2.60 tokens	2.12 tokens	2.12 tokens
SITUATION22	2.12 tokens	2.12 tokens	2.6 tokens	1.50 tokens
SITUATION23	2.60 tokens	1.50 tokens	2.90 tokens	0.78 tokens
SITUATION24	2.90 tokens	0.78 tokens	3 tokens	0 tokens

You will be informed about the outcome of this task at the end of the experiment. Please raise your hand if you have any questions.

Task 3

In this task you will be presented with 10 rows. In each row, you are asked to choose one out of two alternatives. At the end of the experiment, the computer will choose one of these 10 rows at random, and this row will determine your earnings in the following way.

The computer will identify which of the two options A or B did you choose in the selected row. The computer will then select at random one out of chips to determine your earnings.
These chips have value which is

- either 2 tokens or 1.60 tokens if you choose Option A, or
- either 3.85 tokens or 0.10 tokens, if you choose Option B.

In each row, the number of chips with the respective prizes the computer selects from is described below. For example, in row 1 in Option A, the computer chooses one out of 10 chips, where one of these chips has the prize 2 tokens, and 9 of these chips have the prize 1.60 tokens

You will be asked to enter your decision at the computer screen.

Option A	Option B
1/10 of 2 tokens, 9/10 of 1.60 tokens	1/10 of 3.85 tokens, 9/10 of 0.10 tokens
2/10 of 2 tokens, 8/10 of 1.60 tokens	2/10 of 3.85 tokens, 8/10 of 0.10 tokens
3/10 of 2 tokens, 7/10 of 1.60 tokens	3/10 of 3.85 tokens, 7/10 of 0.10 tokens
4/10 of 2 tokens, 6/10 of 1.60 tokens	4/10 of 3.85 tokens, 6/10 of 0.10 tokens
5/10 of 2 tokens, 5/10 of 1.60 tokens	5/10 of 3.85 tokens, 5/10 of 0.10 tokens
6/10 of 2 tokens, 4/10 of 1.60 tokens	6/10 of 3.85 tokens, 4/10 of 0.10 tokens
7/10 of 2 tokens, 3/10 of 1.60 tokens	7/10 of 3.85 tokens, 3/10 of 0.10 tokens
8/10 of 2 tokens, 2/10 of 1.60 tokens	8/10 of 3.85 tokens, 2/10 of 0.10 tokens
9/10 of 2 tokens, 1/10 of 1.60 tokens	9/10 of 3.85 tokens, 1/10 of 0.10 tokens
10/10 of 2 tokens, 0/10 of 1.60 tokens	10/10 of 3.85 tokens, 0/10 of 0.10 tokens

You will be informed about the outcome of this task at the end of the experiment. Please raise your hand if you have any questions.

Task 4

General description:

In this task, your earnings will depend on your decision and the decision of one randomly selected other participant in this experiment. You will not learn the identity of this participant, neither during nor after the experiment.
In this task, one of the subjects in the pair will be assigned the role of SENDER, and the other one will be assigned the role of RECEIVER. We will now explain the payments and the decision procedure.

The payments:

At the beginning of this Task, both SENDER and RECEIVER will receive an endowment of 10 tokens.
Then, SENDER will be asked to make a choice first. SENDER will be asked to choose how many of his/her 10 tokens he/she transfers to RECEIVER.

- SENDER can choose to send either 0, 1, 2 … 10 tokens to RECEIVER.

The tokens will be multiplied by three on the way to RECEIVER, i.e. RECEIVER receives three times as many tokens as SENDER transferred to him/her.

After that, RECEIVER will be asked to make a choice. RECEIVER will be asked how many tokens he/she wants to send back to SENDER from the tokens received. RECEIVER can choose either to send back nothing, or to send back half of the received tokens.

- RECEIVER can choose to send back either one half of the received tokens, or nothing.

At the end of the task, the payments to SENDER and RECEIVER will be made based on the tokens they hold, that means:

SENDER will be paid for

(10 tokens) MINUS (number of tokens transferred to RECEIVER) PLUS (tokens received from RECEIVER)
and
RECEIVER will be paid for

(10 tokens) PLUS (three times number of tokens transferred by SENDER to RECEIVER) MINUS (either half of the received tokens, or zero, depending on RECEIVER's decision)

The decision procedure:
We will now describe the procedure by which you will make your decisions in this Task.
In the experiment, you will be randomly assigned the role of SENDER , or the role of RECEIVER. The computer will match at random subjects into pairs, consisting of one SENDER and one RECEIVER. You will learn your role only at the end of the experiment. Therefore, we will ask you to submit your decision both as SENDER and as RECEIVER. Your decision in the role randomly assigned to you will determine your earnings in the following way.

The decision procedure of sender:
Each SENDER will be faced with a situation of being randomly matched to one out of FOUR possible RECEIVERS. We will ask you, in the role of the SENDER, to submit your decision on how many tokens you choose to send to the RECEIVER. You will do it in SIX possible scenarios. Please be aware that you have an endowment of 10 tokens in every possible scenario. You need to decide how much of this 10 tokens to send to the RECEIVER in each of the six scenarios.

One scenario without information:
In one of these scenarios, you will not be informed about the choices of the four possible RECEIVERS. You will be simply asked to choose the number of tokens to send to the RECIVER. Then one out of the four possible RECEIVERS will be randomly matched to you.

Five scenarios with information:

In five scenarios, you will be able to choose the number of tokens you send to the RECEIVER. You have to choose the number of tokens that you send for each of the following scenarios:

→ none of the four possible receivers returns back half of the received tokens
→ one of the four possible receivers returns back half of the received tokens
→ two of the four possible receivers returns back half of the received tokens
→ three of the four possible receivers returns back half of the received tokens
→ all of the four possible receivers returns back half of the received tokens.

After the four possible RECEIVERS have made their choices, we will count the number of RECEIVERS which chose to send back half of the tokens. This number will then determine which of the five above scenarios (with information) the computer will consider when calculating your earnings for this part of the experiment. Thus, out of these five scenarios, only one can be an actual scenario that is relevant for your earnings. In this actual scenario, one out of the four possible RECEIVERS is then randomly matched with you.

You will submit your decisions at six different computer screens, one for each of the six scenarios.
After your six decisions, the computer will randomly select either the scenario without information, or the one actual scenario with information, to be the scenario that is relevant for your earnings. Depending on your decision, how much to send in this specific scenario, and on the RECEIVER'S individual decision on returning back half or not, your payoff for this task is determined.

The decision procedure of receiver
After the decision made by SENDER, the RECEIVER will make his/her decision.

- DECISION OF RECEIVER IS either RETURN NOTHING or RETURN ONE HALF

Note that RECEIVER will not be informed about how many tokens did SENDER transfer to him/her, but makes only one decision to either send nothing or half of the received tokens back.
At the end of the experiment, the computer will randomly assign the role of SENDER to half of the subjects, and the role of RECEIVER to the other half.
Your payments will depend on the role that is assigned to you, and the decision of the subject matched to you by the computer, in the other role, as described above.

Auxiliary measures
We tested participants' lottery ambiguity preferences, their social preferences and their beliefs regarding the behavior of Trustees in the Trust Game.

To elicit **lottery ambiguity preferences**, each subject made a sequence of 20 pair wise choices between a lottery with a known composition of the urn and a sure option (risk choice list); as well as a sequence of 20 pair wise choices between a lottery with an unknown composition of the urn and a sure option (ambiguous choice list). The sure option increases with each row to a maximum amount of 5 tokens. From both choice lists we define a subject's certainty equivalent as the midpoint of two sure payoffs related to the choice before and at the (last) switching point. For instance when a subject chooses ten consecutive times to draw a ball from the urn before switching to the sure payoff of 2.75 tokens, this subject's certainty equivalent is 2.625 tokens (midpoint between 2.5 and 2.75 tokens). We estimate each subject's lottery ambiguity preferences based on certainty equivalents (Wakker, 2010).

$$\textit{Lottery ambiguity preferences} = (CE_R - CE_A) / (CE_R + CE_A)$$

CE_r and CE_a denote the certainty equivalents of the risk choice list respectively the ambiguous choice list. This measure ranges from -1 (extreme ambiguity seeking) to 1 (extreme ambiguity aversion). A score of 0 indicates ambiguity neutrality. The difference between CE_r and CE_a is divided by the absolute level of risk and ambiguity attitude in order to control for the fact that similar differences in certainty equivalents will weigh more heavily for a risk averse subject than a risk neutral or risk seeking subject (Sutter et al., 2013).

We measure **social preferences** by applying the value orientation task (ring task) (Liebrand, 1984). By collecting 24 decisions on pairs of payoffs this task measures the willingness to increase/decrease the payoff of an anonymous co-player at a cost. All pair of choices can be represented in a circle on adjacent equally spaced coordinates. The horizontal axis of the imaginary circle indicates the amount of money allocated to oneself and the vertical axis indicates the amount of money allocated to the other anonymous person. Summing all decisions, a measure of the unconditional willingness to give or take is obtained. Five roles can be distinguished, namely altruistic subjects (vectors lying between 67.5 – 112.5), cooperators (vectors lying between 22.5 – 67.5), individuals (vectors lying between -22.5 – 22.5), competitors (vectors lying between -67.5 – -22.5) and finally aggressors (vectors lying between -112.5 – -67.5).

We also collected subjects' **beliefs** by administering a non-incentivized questionnaire in which they indicated (on a 5-point Likert scale) how likely they considered each of the scenarios of trustworthiness from the RTG to materialize. The variable beliefs records the most likely scenario of x_0, x_1,…,x_4 that subjects expect. A higher value indicates subjects' optimism about the general trustworthiness in Trustees.
On average, participants can be classified as ambiguity averse (Table 1), individualistic (Table 2) and holding quite pessimistic beliefs with regard to Trustees' reciprocity (Table 3).

Table A1 Lottery ambiguity preferences

Certainty equivalent of the risk lottery minus certainty equivalent of ambiguous lottery, while controlling for the absolute level of risk and ambiguity preferences (range: -1 to 1)		
Normalized ambiguity attitude	Total in % (N=92)	Type
>0	40.22 (37)	Ambiguity averse
0	29.35 (27)	Ambiguity neutral
<0	30.43 (28)	Ambiguity seeking
Mean value	-0.054	

Table A2 Social preferences

Social preferences categorization (angle)	Total in % (N=92)
Cooperative (22.5 – 67.5)	39.13 (33)
Individualistic (-22.5 – 22.5)	51.09 (47)
Competitive (-67.5 – -22.5)	3.26 (3)
Aggressive (< -67.5)	6.52 (6)
Mean Angle	11.0

Table A3 Beliefs with regard to RTG: scenarios that subjects find most likely

RTG scenario	Frequency in % (N=92)
0	0.18 (17)
0.5	0.09 (8)
1	0.12 (11)
1.5	0.02 (2)
2	0.31 (29)
2.5	0.08 (7)
3	0.09 (8)
3.5	0.00 (0)
4	0.11 (10)

Note: When the highest score was attached to more than one RTG scenario, we report the average.

Robustness analyses

We run additional multivariate analyses to show that the main results reported in the paper are robust. First we report the results of analyses where we included the auxiliary measures to the main models reported in the paper (Table 4 and 5). In Table 4 we specifically test for the order in which we implemented our experimental tasks: lottery risk and auxiliary measures either before or after the Trust Game, and the order of the Trust Game treatment (RTG before or after the STG). In Table 5 we control for session fixed effects.

The effect of the RTG risk preferences on transfer in the STG remains valid in both models. The order in which the standard and the risky environment are presented to the subjects in the experiment affects their transfer in the STG. Subjects, who first participated in the RTG, transfer on average 1.5 tokens less in the STG compared to subjects who were first exposed to the STG. This order effect is significant as can be seen in Table 4 by the negative and statistically significant coefficient of the dummy variable indicating an ordering of RTG before STG (equal 1 and 0 otherwise). We also find that Trustors' beliefs about Trustees' return decisions play a role when explaining the variation of transfers in the STG (Table 4 and 5).

Lastly, we excluded all subjects from the regression analyses, who either transferred more than zero tokens and/or less than ten tokens in the scenarios x_0 and x_4, respectively (Table 6). This resulted in a smaller sample of 51 subjects. All our results remain qualitatively valid.

Table A4 Trust and risk: controlling for additional individual measures

Transfer in STG (dependent variable)	Model 1	Model 2	Model 3
Constant	2.842 (0.915)	1.043 (1.406)	1.072 (1.467)
RTG risk Preferences	0.344*** (0.096)		0.367*** (0.090)
Lottery risk preferences		0.364 (0.267)	0.434 (0.270)
Lottery ambiguity preferences	-0.351 (1.395)	-0.617 (1.356)	-0.121 (1.230)
Social preferences	-0.002 (0.015)	-0.002 (0.016)	-0.007 (0.016)
Beliefs	0.703** (0.309)	0.631 (0.313)	0.707** (0.308)
Gender	-0.192 (0.849)	-0.052 (0.914)	0.142 (0.877)
Economic major	-0.064 (0.860)	-0.047 (0.853)	-0.141 (0.827)
Session 1	-0.033 (1.255)	0.103 (1.328)	-0.273 (1.251)
Session 2	-2.008* (1.055)	-1.822 (1.130)	-2.200** (1.049)
Session 3	0.088 (1.163)	0.681 (1.177)	0.101 (1.144)
Session 4	0.069 (1.026)	0.167 (1.092)	-0.308 (0.958)
Session 5	-0.345 (1.181)	0.099 (1.256)	-0.574 (1.148)
N	92	92	92
F test	(11, 80) = 3.32	(11, 80) = 2.07	(12, 79) = 3.63
Prob > F	0,0009	0,0319	0,0002
R - squared	0,1995	0,1596	0,2249

****, **, * significant at the 0.01, 0.05, 0.1 level, respectively. Heteroskedasticity-corrected (robust) standard errors in parentheses.*

Table A5 Trust and risk: controlling for additional individual measures and sessions

Transfer in STG (dependent variable)	Model 1	Model 2	Model 3
Constant	-4.567 (2.045)	1.083 (2.168)	1.072 (1.467)
RTG risk Preferences	13.842*** (3.184)		0.367*** (0.090)
Lottery risk preferences		0.579 (0.380)	0.434 (0.270)
Lottery ambiguity preferences			-0.121 (1.230)
Social preferences			-0.007 (0.016)
Beliefs			0.707** (0.308)
Gender	1.237 (0.834)	0.525 (1.244)	0.142 (0.877)
Economic major	0.582 (1.226)	0.196 (1.547)	-0.141 (0.827)
Session 1	1.510 (1.400)	-0.338 (1.738)	-0.273 (1.251)
Session 2	-1.128 (1.232)	-3.223 (1.100)	-2.200** (1.049)
Session 3	1.359 (1.646)	0.806 (1.668)	0.101 (1.144)
Session 4	0.844 (1.338)	-0.613 (1.698)	-0.308 (0.958)
Session 5	-1.177 (1.67)	-0.796 (1.700)	-0.574 (1.148)
N	51	51	51
F test	(8, 42) = 4.93	(8, 42) = 3,32	(8, 42) = 4.93
Prob > F	0,0002	0,0049	0,0002
R - squared	0,4398	0,1657	0,4398

****, **, * significant at the 0.01, 0.05, 0.1 level, respectively. Heteroskedasticity-corrected (robust) standard errors in parentheses.*

Table A6 Trust and risk: smaller sample (subjects who transferred more than zero tokens and/or less than ten tokens in the scenarios x_0 and x_4, respectively)

Transfer in STG (dependent variable)	Model 1	Model 2	Model 3	Model 4
Constant	-4.567 (2.045)	1.083 (2.168)	-5.219 (2.075)	-5.238 (2.424)
RTG risk Preferences	13.842*** (3.184)		13.357*** (3.360)	11.496*** (3.683)
Lottery risk preferences		0.579 (0.380)	0.216 (0.340)	0.272 (0.324)
Lottery ambiguity preferences				0.001 (0.117)
Social preferences				0.046 (0.030)
Beliefs				0.440 (0.333)
Gender	1.237 (0.834)	0.525 (1.244)	1.394 (0.880)	0.596 (1.010)
Economic major	0.582 (1.226)	0.196 (1.547)	0.489 (1.218)	-0.212 (1.191)
Session 1	1.510 (1.400)	-0.338 (1.738)	1.396 (1.449)	1.758 (1.345)
Session 2	-1.128 (1.232)	-3.223 (1.100)	-1.252 (1.254)	-0.457 (1.128)
Session 3	1.359 (1.646)	0.806 (1.668)	1.332 (1.662)	1.498 (1.583)
Session 4	0.844 (1.338)	-0.613 (1.698)	0.613 (1.411)	-0.245 (1.260)
Session 5	-1.177 (1.67)	-0.796 (1.700)	-1.197 (1.148)	-1.414 (1.503)
N	51	51	51	51
F test	(8, 42) = 4.93	(8, 42) = 3,32	(9, 41) = 4.89	(12, 38) = 7.54
Prob > F	0,0002	0,0049	0,0002	0,0002
R - squared	0,4398	0,1657	0,4458	0,4458

****, **, * significant at the 0.01, 0.05, 0.1 level, respectively. Heteroskedasticity-corrected (robust) standard errors in parentheses.*

2) Appendix – Instructions used for papers:

- **Social sources of uncertainty: an fMRI study: an fMRI study**
- **Anticipating rewards: The power of beliefs in activating an expected reward signal in the ventral striatum**

INTRODUCTION

Thank you for participating in this experiment on decision making. This experiment will last for about 3 hours.

1. The preparations before you go into the MRI scanner last for 1 hour, and consist of:
   - Reading Instructions 'sender-receiver game' and comprehension test.
   - Extra Task related to the sender-receiver game.
   - Reading Instructions 'lottery game' and comprehension test.

2. Then you will play the sender-receiver game and the lottery game in the MRI scanner (1 hour for the experiment and 0.5 hr preparations MRI scanner). In total you will make 96 choices, 48 for the sender-receiver game and 48 for the lottery game. Also, after making all choices, the outcomes of all choices will be revealed to you while still lying in the MRI scanner.

3. After you have finished the experiment, we will start the payment procedure (0.5 hr). You will be paid for multiple randomly chosen decisions you made in these games.

During the experiment, information about the outcomes of your decisions will be expressed in tokens. The amount of tokens that you will earn for these decisions will be converted to Euro's; the following conversion rate applies:

1 token = € 0.10

It is very important that you read these instructions carefully as we will thoroughly explain the experiment to you. You can ask questions for clarification at any moment in time. We ask you to fill in the answer to the comprehension questions which you can find at the end of the instructions for both games. Thereby we can assess if everything is clear to you.
You may read the payment procedure in the attachment of these instructions.

Let us now carefully explain the experiment to you.

The sender-receiver game

In this game two persons will be matched into a pair: one person will be called SENDER and one RECEIVER. Both SENDER and RECEIVER start the game with 10 tokens.

The SENDER has to choose an amount of TRANSFER (in tokens) either:
TRANSFER: 0 - 2 - 4 - 6 - 8 - 10.

- If SENDER chooses **TRANSFER=0**, no interaction between SENDER and RECEIVER takes place, and the outcome is 10 tokens for SENDER and 10 tokens for RECEIVER.
- If SENDER chooses an amount of **TRANSFER (2, 4, 6, 8 or 10)**, interaction between SENDER and RECEIVER will take place in the following way. The chosen level of TRANSFER will be multiplied by 3, and transferred to the RECEIVER. The RECEIVER will thus hold 10 own tokens PLUS 3*transferred tokens. Then RECEIVER will choose to SEND BACK NOTHING or SEND BACK HALF.

EXAMPLE: Let us consider for illustration that SENDER chooses TRANSFER=6. Therefore, SENDER keeps 4 tokens (10 – 6 tokens) for him/herself. The RECEIVER will now hold 10 own tokens PLUS 3*6 transferred tokens = 28 tokens. The outcome of the interaction depends now on the decision of the RECEIVER. RECEIVER can choose either **SEND BACK NOTHING** or **SEND BACK HALF**.

- If RECEIVER chooses **SEND BACK NOTHING**, the outcomes are
    - for SENDER: 10 tokens MINUS transferred tokens.
    - for RECEIVER: 10 tokens PLUS 3*transferred tokens for RECEIVER.
    - In our example: if RECEIVER chooses SEND BACK NOTHING, the SENDER will end up with 4 tokens and the RECEIVER with 28 tokens.
- If RECEIVER chooses **SEND BACK HALF**, the outcomes are
    - for SENDER: 10 tokens MINUS transferred tokens PLUS one half of the RECEIVER's tokens (that is one half of (10 tokens PLUS 3*transferred tokens from SENDER)).
    - for RECEIVER: one half of the RECEIVER's tokens, that is one half of (10 tokens PLUS 3*transferred tokens).
    - In our example: if RECEIVER chooses SEND BACK HALF, the SENDER will end up with 4 tokens PLUS 14 tokens = 18 tokens; and the RECEIVER with 14 tokens.

The more the SENDER decides to TRANFER, the higher the total amount of tokens that the RECEIVER will hold and could potentially send back to SENDER, or keep for him/her self. The outcome depends on the decision of the RECEIVER.

Please see the table below for the outcomes corresponding to each level of TRANSFER.

Chosen level of TRANSFER by SENDER	Receiver will hold:	Outcome of the interaction if RECEIVER chooses **send back half**	Outcome of the interaction if RECEIVER chooses **send back nothing**
0	10	SENDER: 10 RECEIVER: 10	SENDER: 10 RECEIVER: 10
2	16	SENDER: 16 RECEIVER: 8	SENDER: 8 RECEIVER: 16
4	22	SENDER: 17 RECEIVER: 11	SENDER: 6 RECEIVER: 22
6	28	SENDER: 18 RECEIVER: 14	SENDER: 4 RECEIVER: 28
8	34	SENDER: 19 RECEIVER: 17	SENDER: 2 RECEIVER: 34
10	40	SENDER: 20 RECEIVER: 20	SENDER: 0 RECEIVER: 40

In this experiment, **you** will be assigned the role of SENDER.

Information about the RECEIVERS

In a previous session of this experiment (beginning of the second Semester) participants were assigned the role of RECEIVERS and they made **one single choice** between SEND BACK NOTHING and SEND BACK HALF in case they would interact with a SENDER that would choose a level of TRANSFER higher than 0.

You will receive a booklet with information about all participants who made their choice as RECEIVER. You will learn their gender, study background, age, hobbies, relationship status and family background.

For each decision you will make in this game, you will be matched to **one** RECEIVER who will be randomly selected out of a group of 9 RECEIVERS. These 9 RECEIVERS are randomly selected from the total pool of RECEIVERS. For each and every decision a new draw of 9 RECEIVERS will be assigned to you. These 9 RECEIVERS will be indicated to you by displaying their photo silhouettes which were taken from the back while these participants were making their choice as RECEIVER behind the computer in this laboratory (Figure 1).

Figure A1 NINE assigned RECEIVERS

Decisions and screens

When you have seen the silhouettes of the 9 RECEIVERS assigned to you, you have to choose a certain amount of TRANSFER on the actual choice screen.

On this choice screen you can see some information on the choices made by the 9 RECEIVERS assigned to you. Please see Fig. 2 on the next page for an example. In this example you see that out of the 9 RECEIVERS assigned to you 3 RECEIVERS chose to **send back half** of the received tokens (green background), and 6 RECEIVERS chose to **send back nothing** (red background).

For each decision a new draw of 9 RECEIVERS from the total pool of RECEIVERS will be assigned to you. On each decision screen, information about the receivers will be given to you. The RECEIVERS that chose **send back HALF** will be visually represented on the green background, and the RECEIVERS that chose **send back NOTHING** on the red background. Based on the information given to you on the choice screens in the experiment you can select a preferred level of TRANSFER.

However on some choice screens you may learn nothing about the decisions made by the nine assigned RECEIVERS. Please see Fig. 3 for an example of such a case, when no information about the 9 assigned receivers is provided to you. You can recognize such a decision by the grey background.

Please be aware that you start each new decision with 10 tokens again!

Figure A2 Example choice screen of the sender-receiver game WITH INFORMATION

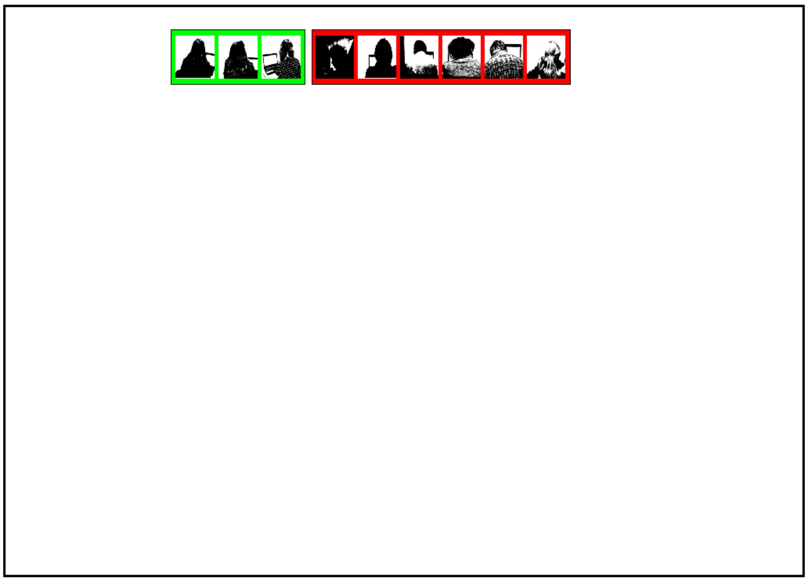
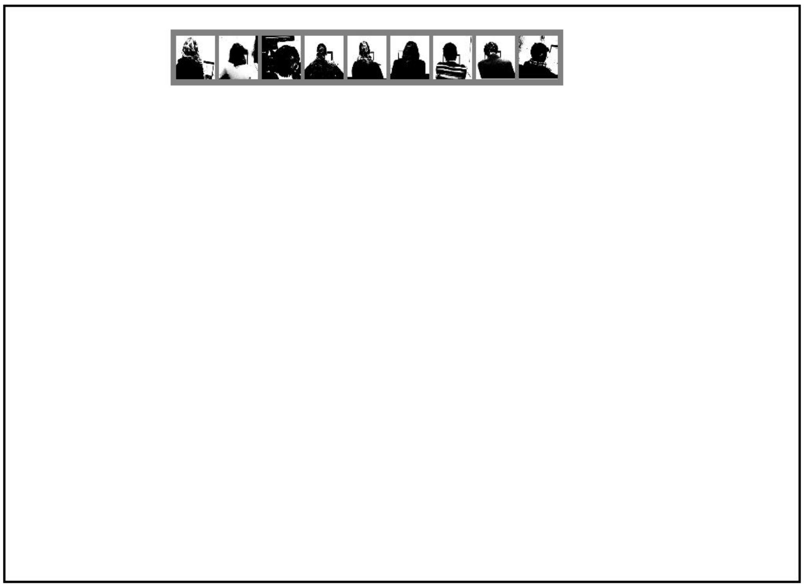


Figure A3 Sender-receiver game WITHOUT INFORMATION



COMPREHENSION TEST: sender-receiver game

Please, answer now the following questions to make sure that you understand the instructions so far. if you have any questions, please let us know by raising your hand.

1. If I choose <u>transfer = 4</u> in the sender-receiver game and it is the case that the RECEIVER randomly assigned to me out of 9 RECEIVERS made a decision to send back half, then my outcome (in tokens) would be: ____________ **(calculate)**
2. If I choose <u>transfer = 4</u> in the sender-receiver game and it is the case that the RECEIVER randomly assigned to me out of 9 RECEIVERS made a decision to send back nothing, then my outcome (in tokens) would be: ____________ **(calculate)**
3. If I choose <u>transfer = 8</u> in the sender-receiver game and 3 out of 9 RECEIVERS assigned to me in this decision choose to send back half, I have a chance of 33% that the specific RECEIVER randomly paired to me in this decision chooses to send back half. That is, I have a chance of 33% that I will earn 19 tokens; and the RECEIVER matched to me will earn 17 tokens. **True or False?**
4. If in one decision, I receive information that 5 out of 9 RECEIVERS assigned to me in this decision choose to send back half, then I will have the same chance of 55% in each consecutive decision that a RECEIVER randomly paired to me in that other decision chooses to send back half. **True or False?**
5. If I choose <u>transfer=0</u> in the sender-receiver game then the choice of the RECEIVER matched to me in this decision will not affect my outcome. **True or False?**
6. When I receive no information about the decisions of the nine RECEIVERS randomly assigned to me in some decision, then information that I received in the previous screens tells me a lot about the chances that a randomly assigned RECEIVER out of these 9 will choose to SEND BACK HALF. **True or False?**

Extra Task 1
1 token = € 0.50 (only for this task!!)

We have explained to you all the details of the sender-receiver game. We also explained to you that the RECEIVERS were asked in a previous experimental session to <u>send back nothing</u> or <u>send back half</u> in case they would interact with a SENDER that would choose a level of TRANSFER higher than 0. We have collected these decisions.

SOCK UNKNOWN
In this task we will first create a SOCK, which we will label SOCK UNKNOWN here. It will consist of the choices made by 9 randomly selected RECEIVERS out of all RECEIVERS who made their choice. We will now demonstrate to you an A4 envelope that contains all RECEIVERS' choices (send back half or send back nothing). You will take (without looking) 9 RECEIVERS from this A4 envelope and put them into the SOCK without looking. This is the SOCK UNKNOWN which will be sealed with a tag.

Prediction
In this extra task we ask you to indicate how many RECEIVERS – out of the 9 RECEIVERS in your SOCK UNKNOWN – you think chose SEND BACK NOTHING respectively SEND BACK HALF. You may indicate this in the table like the one below with a number between 0-9. **You may only choose the numbers 0 – 1 – 2 – 3 – 4 – 5 – 6 – 7 – 8 – 9.**

How many RECEIVERS do you think chose SEND BACK NOTHING	How many RECEIVERS do you think chose SEND BACK HALF
Left answer box	*Right answer box*

Example
Let us assume that you believe the composition of the SOCK UNKNOWN consists of 2 RECEIVERS that chose send back nothing, and thus 7 RECEIVERS that chose send back half. Then please write the numbers 2 and 7 in the table, respectively in the left and right answer box. **The numbers must always add up to 9.**

The payment procedure for this task is designed in such a way that you are best advised to indicate the composition of the SOCK UNKNOWN that correspond to what you think is the true situation.
You may read the attachment (back of this page) if you wish to know the payment procedure.

ATTACHMENT – Explanation payment procedure

At the end of this experiment you will draw one RECEIVER out of the SOCK UNKNOWN and the decision made by this RECEIVER will be compared to your prediction. We will pay you for the accurateness of your prediction. The better you predict the composition of the SOCK UNKNOWN, the more chance you have to draw a RECEIVER matching your prediction.
Note that the payment procedure is designed in such a way that you are best advised to indicate the composition of the SOCK UNKNOWN that correspond to what you think is the true situation.

Your earnings for the correctness of your prediction will be calculated in the following way:
Let us assume the predictions given in the example above (2 for left answer box and 7 for right answer box) and let us also assume that the RECEIVER you draw from the UNKNOWN SOCK chose to send back HALF. Your earnings would then be: $10 – 5*(1-7/9)^2 – 5*(2/9)^2 = 9.5$ tokens. In other words, we give you 10 tokens to start with and subtract it with the inaccurateness of your **correct** prediction about the RECEIVER's choice = $5*(1-7/9)^2$ and lastly subtract it with the number you assigned to the **incorrect** prediction with regard to the RECEIVER's choice = $5*(2/9)^2$.

Please note that the best prediction you can make is when you correctly predict the choice behavior of the RECEIVER you will randomly draw from the SOCK UNKNOWN by assigning the number 9 to the correct RECEIVER's choice. In that case you earn 10 tokens. The worst that can happen in this task is when you believe in an incorrect choice behavior of the RECEIVER you will randomly draw from the SOCK UNKNOWN and therefore decide to assign the number 9 to this outcome. Then your earnings will be 0 tokens in this task.

The best thing you can do in this task is to state your true beliefs about what you think are your chances to face a RECEIVER from the SOCK UNKNOWN that chose send back half and send back nothing.

How many RECEIVERS do you think chose SEND BACK NOTHING	How many RECEIVERS do you think chose SEND BACK HALF

Task 2

In this experiment, you will make decisions in two types of games: sender-receiver game and a lottery game. Before, we explained to you the details of sender-receiver game, please bear this in your mind:

Both games have many similarities, AND one important distinction.

- In the sender-receiver game, you will affect the payoffs of one other person, and this person will affect your payoffs. <u>You interact with a human being in the sender-receiver game.</u>
- In the lottery game, you will affect the payoffs of one other person, but that person cannot affect your earnings. Instead of that, a randomized outcome of a computer will affect your earnings. <u>You interact with a computer in the lottery game</u>.

Lottery game

In this game there is a DECISION MAKER and a computerized lottery device, namely an URN filled with 9 marbles. The DECISION MAKER starts the game with 10 tokens. The starting amount of 10 tokens has also been placed in the computerized lottery device.

Remember that in the lottery game your choice affects the outcome of one other person, called the RECIPIENT here.

The DECISION MAKER has to choose an amount of TRANSFER (in tokens) either: TRANSFER: 0 - 2 - 4 - 6 - 8 - 10.

- If DECISION MAKER chooses **TRANSFER=0**, no interaction between DECISION MAKER and the computerized lottery device takes place, and outcome of the interaction is 10 tokens for DECISIONMAKER and 10 tokens for RECIPIENT.
- If DECISIONMAKER chooses a certain level of **TRANSFER (2, 4, 6, 8, or 10)**, these tokens of DECISION MAKER will be multiplied by 3, and placed into a computerized lottery device. The outcome of the interaction depends now on the outcome of this lottery, generated by COMPUTER. It can either happen that the random lottery draws a **WINNING COLOR** or **LOSING COLOR** MARBLE from the urn.

Let us assume for illustration purposes that DECISION MAKER chooses TRANSFER=4. The DECISION MAKER chooses to transfer 4 tokens to be placed into the computerized lottery device and therefore keeps 6 tokens (10 – 4 tokens) for him/herself. The lottery will thus hold 10 starting tokens PLUS 3*4 transferred tokens = 22 tokens.
The outcome of the interaction depends now on the outcome of the lottery. Following the example with TRANSFER=4, the outcomes will be:

  - If the computerized lottery device draws a **LOSING COLOR** marble, the outcomes are:
    - for DECISION MAKER: 10 tokens MINUS transferred tokens (= 6 tokens).
    - for RECIPIENT: the amount of tokens the computerized lottery device holds, which is 10 tokens PLUS 3*transferred tokens from DECISION MAKER (= 22 tokens).

- If the computerized lottery device draws a **WINNING COLOR** marble, the outcomes are:
  - for DECISION MAKER: 10 tokens MINUS transferred tokens PLUS one half of the tokens hold by the computerized lottery device (17 tokens).
  - for RECIPIENT: one half of the tokens hold by the computerized lottery device (11 tokens).

The more the DECISION MAKER decides to TRANFER, the higher the total amount of tokens placed in the lottery device and the more can be returned if a marble with a winning color is randomly selected, or will be retained by the lottery, and distributed to the RECEPIENT, if the marble is a losing color. Please see the table on the next page for the outcomes corresponding to each chosen levels of TRANSFER in the lottery game. DECISION MAKER is shorted for DM in the table below.

Chosen level of TRANSFER by DECISION MAKER	Amount of tokens placed in the lottery:	Outcome of the interaction if **winning color** marble is drawn from the urn (in tokens)	Outcome of the interaction if **losing color** marble is drawn from the urn (in tokens)
0	10	DM: 10 RECEPIENT: 10	DM: 10 RECEPIENT: 10
2	16	DM: 16 RECEPIENT: 8	DM: 8 RECEPIENT: 16
4	22	DM: 17 RECEPIENT: 11	DM: 6 RECEPIENT: 22
6	28	DM: 18 RECEPIENT: 14	DM: 4 RECEPIENT: 28
8	34	DM: 19 RECEPIENT: 17	DM: 2 RECEPIENT: 34
10	40	DM: 20 RECEPIENT: 20	DM: 0 RECEPIENT: 40

In this experiment, **you** will be assigned the role of DECISION MAKER.

Information about the RECEPIENTS
In the lottery game your choice affects the outcome of one other person, called the RECIPIENT, but the RECEPIENT cannot affect your outcome. Participants came into the laboratory (beginning of this month) and read the instructions of the lottery game. At the end of the instructions they were informed about their role as RECEPIENT. All participants signed a consent form and filled in a questionnaire with details about their gender, study background, age, hobbies, relationship status and family background. You will receive a booklet with all RECEPIENTS details. You will be matched to **one** RECEPIENT during all choices you make in the lottery game.

Information about the URN
In this game the computerized lottery device is an urn filled with 9 marbles. There are 9 different colors each marble could have: yellow, orange, blue, pink, purple, brown, white, grey and black. There are two types of URNS in this game, namely a KNOWN URN and an UNKNOWN URN. The KNOWN URN is filled with 9 marbles, each of a different color (Figure 4) The UNKNOWN URN is also filled with 9 marbles but the color of each marble is unknown to you. The computer randomly selects 9 marbles into the UNKNOWN URN from a total of 81 marbles consisting of 9 yellow, 9 orange, 9 blue, 9 pink, 9 purple, 9 brown, 9 white, 9 grey and 9 black marbles. In Figure 5 you see an example of an UNKNOWN URN, which in this case is composed of 2 blue marbles, 3 yellow marbles, 4 brown marbles and 1 purple marble. Figure 5 is an

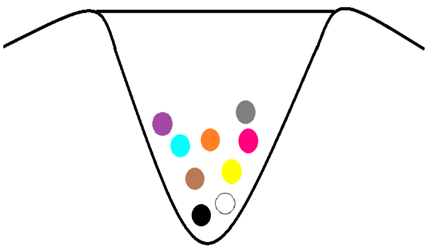


Figure A4 KNOWN urn: ***Each marble has one color.***

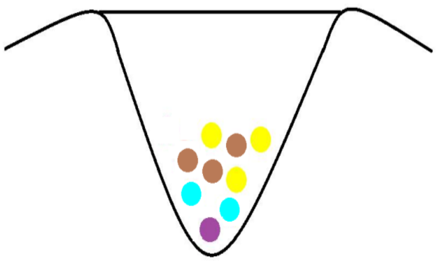


Figure A5 An example of a possible composition for the UNKNOWN urn:
Each marble color is determined at random. Colors can repeat themselves in any way.

illustration how the composition of an UNKNOWN URN could look like. Any combination with 9 different colors is possible.

For each decision you will make in this game **one** marble will be drawn from the urn. Remember that the KNOWN urn contains all 9 colors. However if the urn is UNKNOWN, the 9 marble can have any possible combination with 9 different colors.
In this experiment we will display the following picture (Figure 6) to inform you that you are playing the lottery game with the computerized lottery device, namely the urn filled with 9 marbles.

Figure A6 Nine assigned marbles in Lottery game

Decisions and screens

After you have seen the urn, you have to choose a level of TRANSFER on the actual choice screen.
On the choice screens you are able to recognize the two types of urns. If you see marbles that do not have any color (because they are unknown) on a grey background, you will learn that the computerized lottery device for this decision stems from an UNKNOWN urn. Please see Figure 7 for an illustration of this choice screen. For each new decision of a lottery game WITHOUT information, the computerized lottery device will randomly select 9 marbles into the UNKNOWN urn.

If you see information which marbles from the 9 colored marbles in the urn are **winning colors** (green background) and which are **losing colors** (red background), you will learn that the computerized lottery device for this decision is a KNOWN urn. In Figure 8 on the next page you can indicate that out of the 9 marbles in the urn 6 marbles have **winning colors**, and 3 marbles have **losing colors**. On each new decision screen of a lottery game WITH information, information is given about the amount of marbles that have winning colors and losing colors. This will be visualized by the green background respectively the red background.
Based on the information given to you on the choice screens in the experiment you can select a preferred level of TRANSFER.

Please be aware that you start each new decision with 10 tokens again!

Figure A7 Lottery game WITHOUT INFORMATION

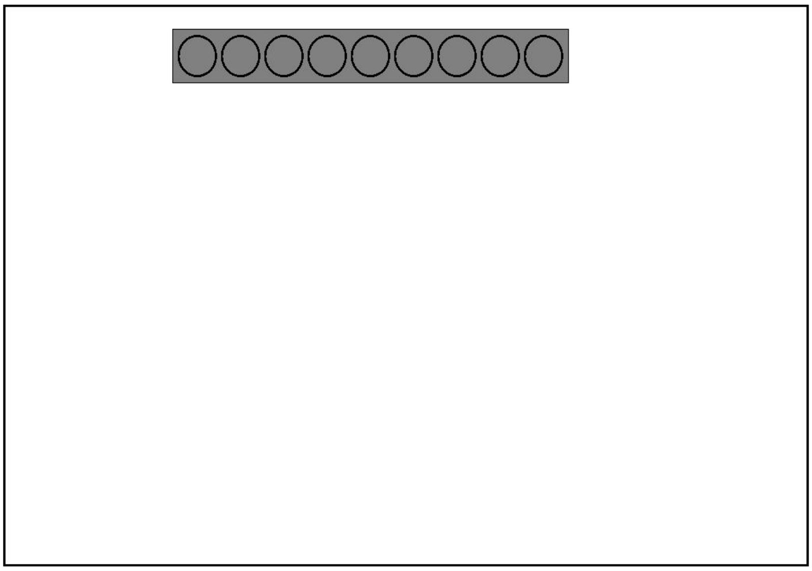
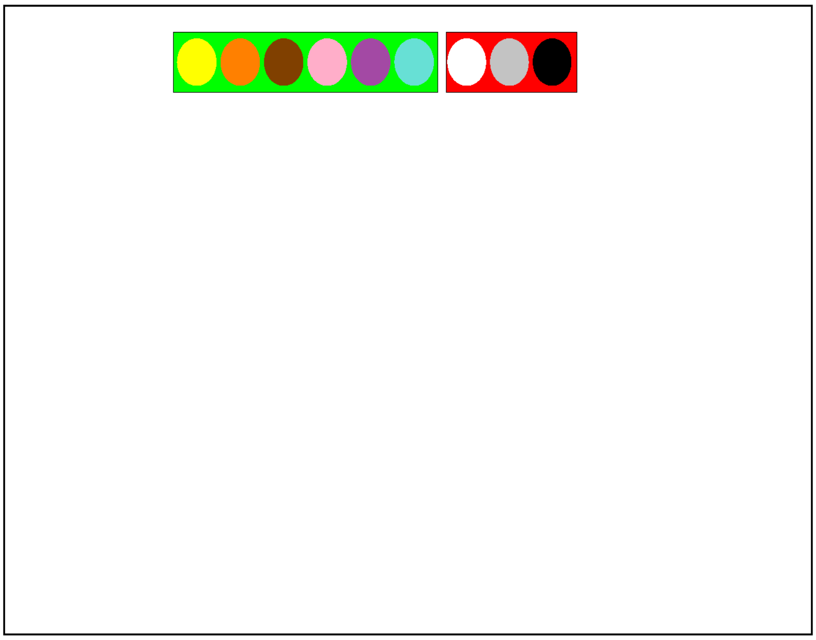


Figure A8 Example choice screen of the lottery game WITH INFORMATION



Marbles with winning and losing colors
Before the experiment you have filled in a color table. Please see the table below for your color table. The colors you selected in each row have been implemented in the computerized lottery device. Let us work out the example from Figure 8. Here you learn that you face 6 marbles that have a winning color and 3 marbles that have a losing color. Please see line 6 in the table below. The colors you selected are: yellow, orange, brown, pink, purple and blue. The computerized lottery device determines which colors are winning or losing colors based on the color table you filled in, as you can see in Figure 8. Please let us give a second example. If you need to make a choice in the lottery game and information on the choice screen tells you that 1 marble has a winning color (on green background) and 8 marbles have a losing color (on red background), then the computerized lottery device is programmed to define the color yellow as winning color.

When you have to make a choice in the lottery game WITHOUT information, **5 colors** are defined as winning colors. Please see line 5 in the color table below for the colors the computerized lottery device will assess as winning colors for the 9 marbles with unknown colors in the UNKNOWN urn.

Therefore the winning colors for the UNKNOWN urn are: brown, blue, grey, white and black. If the unknown urn would be composed as in Fig. 5 five marbles have a winning color. Or, to give another example, if the UNKNOWN urn would be composed of 7 pink marbles and 2 yellow marbles, no single marble in the unknown urn has a winning color.

	yellow	orange	brown	pink	purple	blue	grey	white	black
1	X								
2							X	X	
3						X		X	X
4		X	X	X	X				
5			X			X	X	X	X
6	X	X	X	X	X	X			
7	X	X	X	X		X		X	X
8	X	X	X	X	X	X	X	X	

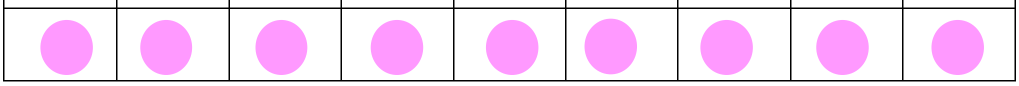
COMPREHENSION TEST: lottery game

1. In the lottery game, I will be matched to one other person, the RECIPIENT, and this person can affect the outcome of my decision should I choose TRANSFER. **True or False?**
2. Suppose that in the lottery game with the KNOWN urn, you choose TRANSFER=2, and the computer randomly selected one marble from the lottery composed of 9 marbles, and this marble was COLORED BY A WINNING COLOR. What is your outcome in tokens in this case? __________**(calculate)** And what is the outcome in tokens of the RECIPIENT randomly matched to you, that makes no decisions in the lottery game? __________**(calculate)**

3. Suppose that in the lottery game with the KNOWN urn, you choose TRANSFER=2, and the computer randomly selected one marble from the lottery composed of 9 marbles, and this marble was COLORED BY A LOSING COLOR. What is your outcome in tokens in this case? _________**(calculate)** And that is the outcome in tokens of the RECEPIENT randomly matched to you, that makes no decisions in the lottery game? _________**(calculate)**
4. Suppose you receive information that out of these 9 marbles 6 were colored by some winning color, and 3 were colored by some losing colors. If you choose <u>TRANSFER=10</u>, what is the chance that the outcome of this decision will be 20 tokens for you? _______________ AND, what is the chance that the outcome of this decision will be 20 tokens for the RECIPIENT randomly ASSIGNED to you? _______________
5. How many colors are winning colors in the UNKNOWN URN? ___ Which colors are the winning colors for the UNKNOWN URN? _______________
6. Consider now the following possible lotteries, and circle POSSIBLE/IMPOSSIBLE for each of them, based on whether the computerized lottery device could generate such an UNKNOWN URN in the lottery game WITHOUT information. Also please indicate how many marbles in these lotteries have a winning color.

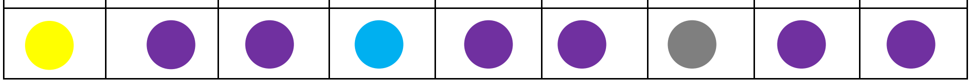
Lottery 1: Possible / Impossible. How many <u>marbles</u> with winning colors are in this UNKNOWN urn? ___

Marble 1	Marble 2	Marble 3	Marble 4	Marble 5	Marble 6	Marble 7	Marble 8	Marble 9



Lottery 2: Possible / Impossible. How many <u>marbles</u> with winning colors are in this UNKNOWN urn? ___

Marble 1	Marble 2	Marble 3	Marble 4	Marble 5	Marble 6	Marble 7	Marble 8	Marble 9

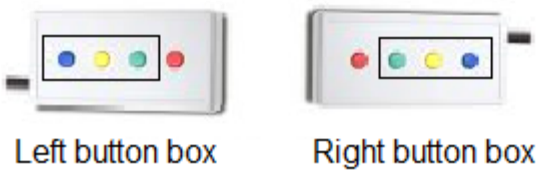


Lottery 3: Possible / Impossible. How many <u>marbles</u> with winning colors are in this UNKNOWN urn? ___

Marble 1	Marble 2	Marble 3	Marble 4	Marble 5	Marble 6	Marble 7	Marble 8	Marble 9

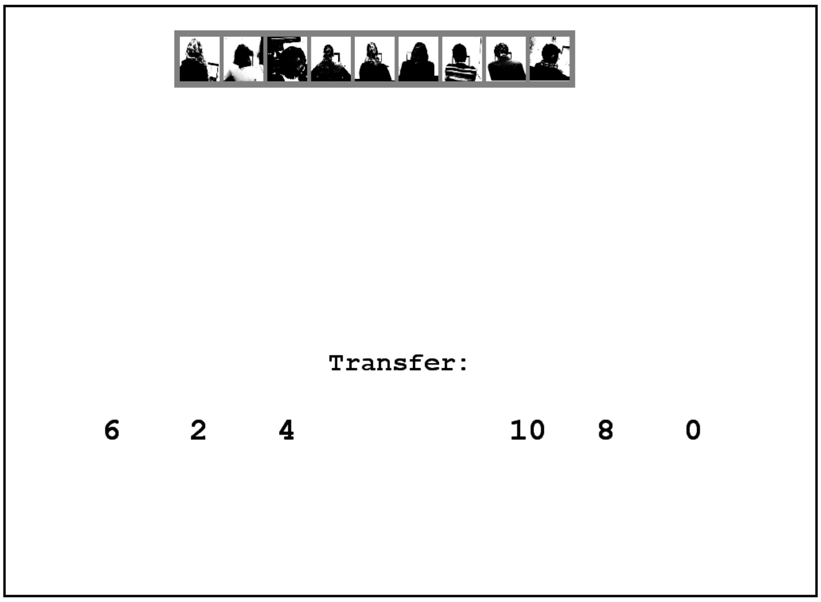
How to indicate your responses in the MRI scanner?

Once you see a choice screen you have **7 seconds** to think about the level of transfer. After 7 seconds the response options appear in the following way (Figure 9). Please push one of the far most three left buttons on your **left** button box for the first three options of Transfer level (in this case 6, 2 and 4) and one of the far most three right buttons on your **right** button box (in this case 10, 8 and 0).



The numbers related to the six levels of TRANSFER do NOT have a fixed position on the choice screen, but will be presented in a random fashion for every response. Just remember that the far most three left buttons on your left button box represent the first three displayed options of Transfer level and the far most three right buttons on your right button box represent the last three displayed options of TRANSFER.
You have to indicate your level of transfer **within 2 seconds,** so please realize that you have to actually make your choice in the 7 seconds time window when you see the choice screen, and simply indicate your choice immediately when the response options appear.

Figure A9 Example of response option



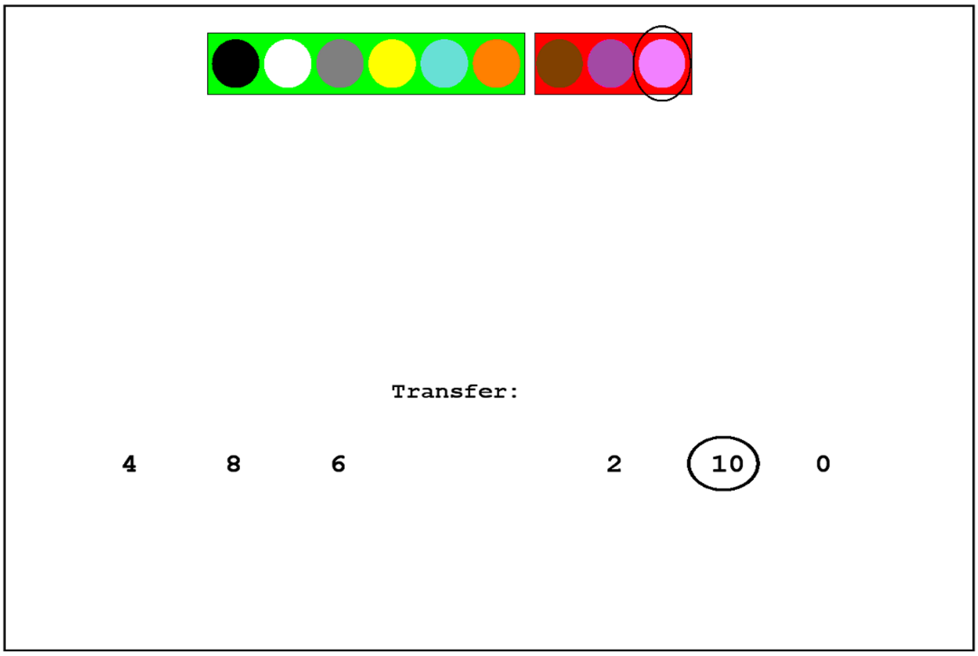
After you indicated your preferred level of TRANSFER, a circle will appear around the selected Transfer on the choice screen. The experiment will continue automatically to the next choice.

At the beginning of the experiment you will have the chance to practice with the button responses.

Outcomes of your choices in the MRI scanner
Once you have made all your decisions we will show you the outcomes for <u>each and every</u> choice you made in this experiment. First we will inform you if the outcome you will see stems from a choice from the sender-receiver game or the lottery game. Then we will remind you of the actual choice screen and the decision you made yourself by putting a **black** circle around the chosen level of TRANSFER. Lastly we will indicate if the computer draws a marble with a winning or losing color (in the lottery game) or a RECEIVER that chose send back half or send back nothing (in the sender-receiver game).

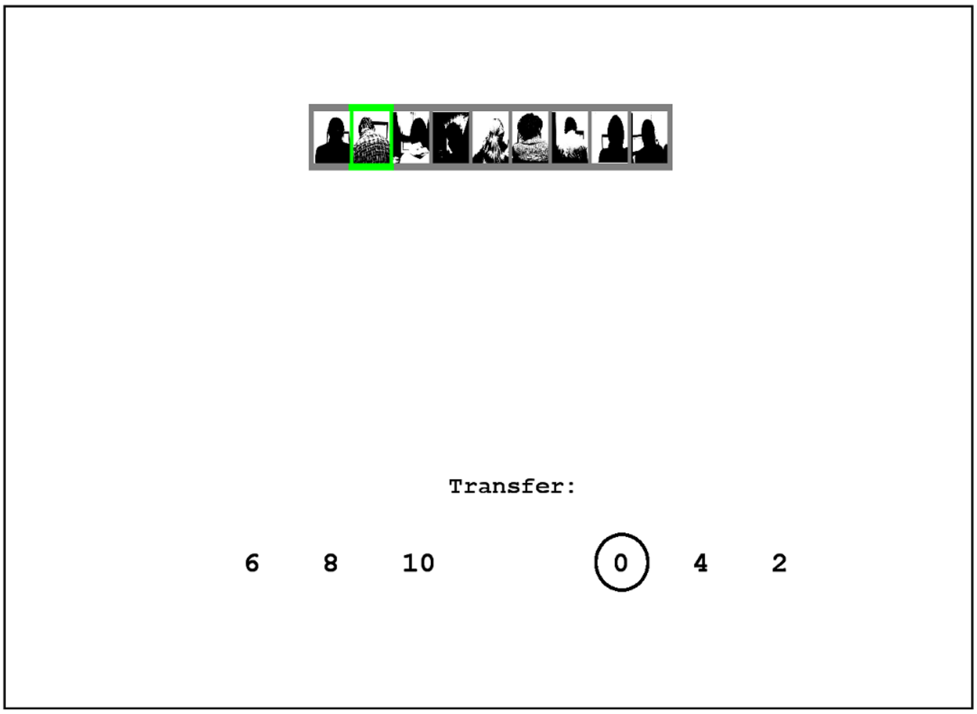
Please see Figure 10 for an example of an outcome from the lottery game WITH information. The marble drawn by the computer is circled. As this selected marble is placed on a red background, you can indicate that a losing marble has been drawn.

Figure A10 Example outcome (in lottery game WITH information)



On the other hand, if you face an outcome from either the lottery game or the sender-receiver game WITHOUT information, a grey background is visible. You can indicate the selected marble (in the lottery game) or selected RECEIVER (in the sender-receiver game) from the red or green background that will be highlighted for only one marble, or one RECEIVER. Please see Figure 11 for an example of an outcome stemming from the sender-receiver game WITHOUT information. The computer selected the second RECEIVER, and as this selected RECEIVER is highlighted by a green background, you will learn that this RECEIVER chose send back HALF. A similar process for the lottery game WITHOUT information will be conducted where either a red or green background will surround the selected marble indicating that the marble is respectively a losing versus a winning color.

Figure A11 Example outcome (in sender-receiver game WITHOUT information)



After you have seen 5 outcomes from the lottery game and 5 choices from the sender-receiver game, the computer will randomly draw 1 outcome from <u>both</u> games and your earnings will be displayed. All earnings will be added and paid to you at the end of the experiment.

3)
Appendix - Ambiguity attitudes and borrowing behavior

Section 1

In this section we provide additional descriptive analyses and perform robustness analyses.

Table A7 shows correlations between our most important experimental variables. Similar to previous research we also find quite some correlations between our measures (Dimmock et al., 2015a; 2015b). The indices of ambiguity aversion and insensitivity are significantly positively correlated. Risk is positively correlated with ambiguity aversion, and weakly with insensitivity. As financial literacy and scores on the cognitive reflection test are both negatively correlated with ambiguity aversion and insensitivity, ambiguity attitudes can somewhat be explained as a cognitive bias (as also put forward by Wakker (2010)). Surprisingly general optimism and pessimism do not correlate with matching probabilities of 0.1, respectively 0.9. This indicates that general optimism and pessimism are different from the optimism and pessimism labels we use when we refer to participants, that respectively overweight and underweight likelihoods of 0.1 and 0.9.

Table A8 shows that bivariate correlations between ambiguity aversion (index b) and risk, financial literacy and scores on the cognitive reflection test hold when controlling for other demographic variables. Only the effect of risk remains prevalent, however, when explaining insensitivity in a multivariate model.

Secondly, we perform several robustness checks to validate the main findings of our study. In this study we used four different production methods to construct urns U2 and U10. These production methods were implemented as four separate treatments, randomized over 17 different sessions. In a companion paper we focus on the question if ambiguity attitudes are influenced by the construction of an ambiguous urn via a between-subjects design. The four different production methods are: unknown, human, compound and nature. In the unknown treatment we created the urns U2 and U10 before participants entered the laboratory, and we did not tell them anything with regard to the production of these urns. In the human treatment we randomly selected two participants from the session. These participants could create urn U2 and urn U10 in any composition they pleased. After they had composed the urns, they were kindly requested to leave the experiment. In the compound treatment the underlying uniform probability distribution from which the urns arise is explicitly detailed. Finally, in the nature treatment the colored marble composition of the urns were determined by a number corresponding to a temperature in a set of different cities around the world. In Table A9 we reran our main OLS regression model with three dummy variables relating to the production methods (we left the unknown production method out as benchmark). We also reran the same model by adding all sessions as separate dummy variables (not shown in a model here). The main results presented in this study remain qualitatively valid.

Table A7: Correlation matrix

Variable						
	Index b	Index a	AA01	AA05	AA09	Risk
Index b	1					
Index a	0.321***	1				
AA01	0.471***	-0.598***	1			
AA05	0.732***	-0.059	0.354***	1		
AA09	0.674***	0.881***	-0.148**	0.136**	1	
Risk	0.132**	0.108*	0.019	0.056	0.145**	1
Optimism	-0.074	-0.034	-0.038	-0.033	-0.064	-0.076
Financial Literacy	-0.191***	-0.122*	-0.081	-0.055	-0.198**	0.065
Cognitive reflection test	-0.234***	-0.129**	-0.054	-0.172***	-0.190***	0.086

***, **, * significant at the 0.01, 0.05, 0.1 level, respectively.

Table A8: OLS regression ambiguity attitude with demographic variables					
	Index b	Index a	AA0.1	AA0.5	AA0.9
Risk aversion	0.136** (0.055)	0.157* (0.088)	0.011 (0.034)	0.056 (0.043)	0.136** (0.055)
Financial literacy	-0.026** (0.012)	-0.022 (0.019)	-0.009 (0.007)	-0.003 (0.010)	-0.026** (0.012)
Cognitive reflection test	-0.065*** (0.021)	-0.052 (0.033)	-0.008 (0.012)	-0.040** (0.016)	-0.050** (0.021)
Optimism	-0.002 (0.002)	-0.001 (0.003)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.002)
Income	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Age	0.001 (0.003)	-0.003 (0.004)	0.001 (0.001)	-0.001 (0.002)	-0.001 (0.003)
Female	0.009 (0.015)	0.010 (0.024)	0.002 (0.009)	0.003 (0.012)	0.009 (0.015)
Economics study	-0.003 (0.019)	-0.033 (0.031)	0.011 (0.012)	-0.001 (0.015)	-0.015 (0.019)
Siblings	0.007 (0.006)	0.007 (0.010)	-0.002 (0.004)	0.008* (0.005)	0.004 (0.006)
Living expenses	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Constant	0.120 (0.078)	0.321 (0.124)	-0.038 (0.048)	-0.001 (0.061)	0.219 (0.078)
Observations	228	228	228	228	228
F-test	F(10,217) = 2.89	F(10,217) = 1.24	F(10,217) = 0.42	F(10,217) = 1.17	F(10,217) = 2.54
Prob > F	0.0021	0.2675	0.9376	0.3132	0.0066
R-squared	0,117	0,054	0,019	0,057	0,105

****, **, * significant at the 0.01, 0.05, 0.1 level, respectively. Standard errors reported in parentheses.*

Table A9: Robustness checks for production method				
Amount	(1)	(2)	(3)	(4)
Index b	23.641		82.746	80.480
	(107.735)		(112.893)	(115.511)
Index a		16.339	38.628	43.297
		(70.685)	(71.094)	(72.199)
Do you borrow	440.267***	386.669***	425.029***	427.141***
	(26.034)	(36.897)	(36.904)	(37.465)
Borrow*IndexB	-503.868***		-655.691***	-643.101***
	(172.384)		(179.472)	(181.946)
Borrow*IndexA		9.660	105.922	96.566
		(119.575)	(121.834)	(123.330)
Risk aversion				-15.116
				(71.368)
Financial literacy				9.772
				(15.956)
Cognitive reflection test				-10.446
				(27.647)
Income			-0.053*	-0.055*
			(0.029)	(0.030)
Study years			10.770***	10.700***
			(4.041)	(4.086)
Female			-17.824	-17.868
			(18.983)	(19.622)
Economic study			55.161**	51.692*
			(23.790)	(25.008)
Siblings			16.784**	16.728*
			(7.850)	(7.952)
Live on own			40.693*	40.842*
			(23.230)	(23.463)
Human	-13.828	-19.718	-6.494	-6.646
	(26.182)	(27.664)	(26.527)	(26.866)
Compound	38.659	34.004	43.884	43.915
	(26.182)	(27.244)	(26.155)	(26.314)
Nature	26.406	29.137	36.501	35.759
	(26.501)	(27.206)	(26.201)	(26.380)
Constant	-16.572	-16.417	-87.386	-95.480
	(23.475)	(29.155)	(38.652)	(67.075)
Observations	228	228	228	228
F test	F (6,223) =	F (6,223) =	F (14,213) =	F(17,210) =
Prob > F	0.0000	0.0000	0.0000	0.0000
Adj. R-squared	0.638	0.618	0.661	0.657

****, **, * significant at the 0.01, 0.05, 0.1 level, respectively. Standard errors reported in parentheses.*

Section 2

Instructions

Introduction

Welcome to this experiment. In this experiment, you will make several decisions. You can earn money depending on the decisions that you will make. For this reason, it is very important that you read these instructions carefully. Additionally to your earnings, you will ALWAYS receive € 4 for your participation in this experiment. You will be paid in cash at the end of the experiment. This payment will be done in private, and thus no other participant will learn how much you earned.
Please note that you are not allowed to communicate with other participants in this experiment. Also please turn off your cell phone to avoid any distractions and remain seated and quiet during the course of the experiment. If at any moment in time you have a question, please raise your hand and an experimenter will come to you.

This experiment consists of **four** independent tasks and a questionnaire at the final end. At the beginning of each new task, you will receive instructions. At the final end of this experiment, the computer will randomly select **one** choice from one of the four tasks. This selected choice will be played out for real in order to determine your earnings. Thus, you should take all tasks seriously as any of the four tasks can determine your payoff at the end.
The first three tasks in this experiment involve lotteries with urns filled with 100 chips of different colors. One urn is filled with 100 chips and is composed in any combination of 2 colors: green and yellow (called **U2**) and another urn has also 100 chips but can be composed in any combination of up to 10 colors: red, yellow, grey, green, blue, purple, pink, orange, light green and black chips (called **U10**). Thus the urn can either contain only one color or two colors, three, four, etc. or all ten colors with any possible number of chips per color. We will produce both these urns as follows.

Production of the urns
Urn U2 is already produced and has an unknown composition of green and yellow balls. Please see urn U2 here.
Urn U10 is also already produced and has an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips. Please see urn U10 here.

These two urns will be used in the following three tasks. U2 will be used in the first task and U10 in task 2 and 3.

Let us now carefully explain the first task of this experiment to you.

TASK 1

In this task you will make several decisions between two different urns each filled with 100 chips. Let us first inform you about these urns.

Urns
In this task there are two urns, named 'urn U2' and 'urn K2'. Urn U2 and urn K2 are each filled with 100 chips. Each chip is either green or yellow.

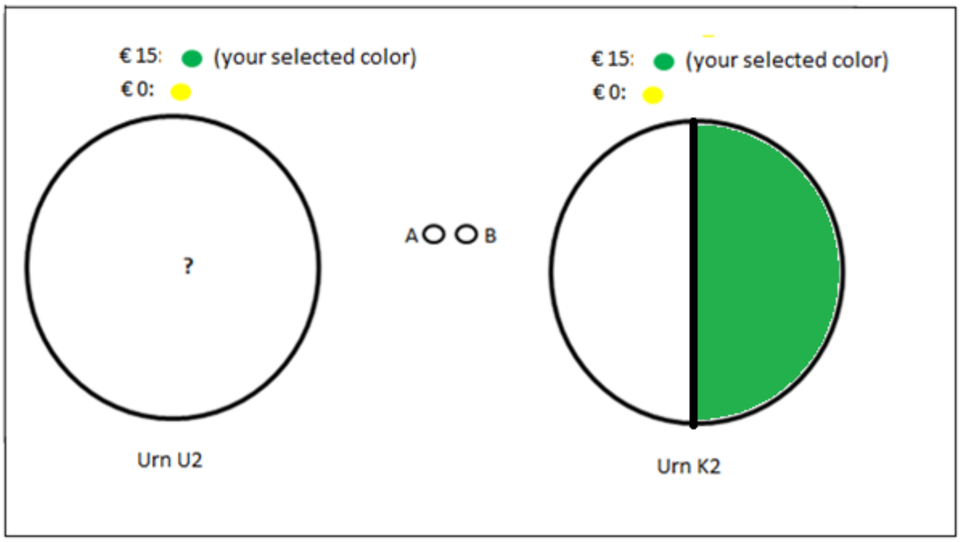
- Urn K2 has a fixed composition of green and yellow chips which will be described to you below.
- Urn U2 was produced at the beginning of this experiment and has an unknown composition of green and yellow chips.

Your decisions

Part 1
In part 1 of this task you have to chose between a draw from urn U2, which we produced at the beginning of the experiment, and urn K2. Remember, that both urns have 100 chips that can either have a green or yellow color. In urn U2 you do not know how many chips are of the one or the other color. In part 1 of this task urn K2 has exactly 50 green and 50 yellow chips. See the screen shot below for an illustration of this task. Remember that you have selected a color right at the start of the experiment. In the screenshot we assume, but only for illustration purposes, that you have selected the color green at the beginning of the

experiment. In part 1 of this task you simply have to choose from which of the two urns you would like to draw a chip (without looking): from urn U2 (Option A) or from urn K2 (Option B).
If part 1 of this task is selected at the end of the experiment to determine your payoff, you can draw a chip from the urn you have chosen (without looking). If the drawn chip has the color you selected at the beginning of the experiment, you will win €15. If the drawn chip has the other color, you win nothing (€0).

Figure 1 Choice screen Part 1 (with <u>green simply as illustration</u>)



Part 2
After the choice in part 1, you will make several choices in part 2 of this task where you will again decide if you wish to draw a chip from Urn U2 or Urn K2. We again assume here for illustration purposes that you had selected green at the beginning of the experiment. Please see Figure 2 for a screenshot of the choice screen on which you may indicate your choices.
As you can see in Fig 2 you will have to make 20 choices. These are all displayed on one screen. In every choice you will have to decide between Urn U2 and Urn K2. Urn U2 is the urn produced at the

beginning of the experiment. Just as a reminder, Urn U2 has 100 chips in an unknown composition of green and yellow marbles. Urn K2 also has 100 chips, but in a composition you will know. For every choice you will be informed how many of the 100 chips in urn K2 have the color you selected at the beginning of the experiment (in the screen shot below it is green). The remaining marbles are then yellow.

Figure 2 Choice screen Part 2 (with <u>green simply as illustration</u>)

Choice	Option A Urn U2	Your choice:	Option B Urn K2
1		A ○ ○ B	€ 15: 23 ● chips, €0 otherwise
2		A ○ ○ B	€ 15: 26 ● chips, €0 otherwise
3		A ○ ○ B	€ 15: 29 ● chips, €0 otherwise
4	€ 15: ● (your selected color)	A ○ ○ B	€ 15: 32 ● chips, €0 otherwise
5	€ 0: ●	A ○ ○ B	€ 15: 35 ● chips, €0 otherwise
6		A ○ ○ B	€ 15: 38 ● chips, €0 otherwise
7		A ○ ○ B	€ 15: 41 ● chips, €0 otherwise
8		A ○ ○ B	€ 15: 44 ● chips, €0 otherwise
9		A ○ ○ B	€ 15: 47 ● chips, €0 otherwise
10		A ○ ○ B	€ 15: 50 ● chips, €0 otherwise
11	?	A ○ ○ B	€ 15: 53 ● chips, €0 otherwise
12		A ○ ○ B	€ 15: 56 ● chips, €0 otherwise
13		A ○ ○ B	€ 15: 59 ● chips, €0 otherwise
14		A ○ ○ B	€ 15: 62 ● chips, €0 otherwise
15		A ○ ○ B	€ 15: 65 ● chips, €0 otherwise
16		A ○ ○ B	€ 15: 68 ● chips, €0 otherwise
17		A ○ ○ B	€ 15: 71 ● chips, €0 otherwise
18	Urn U2	A ○ ○ B	€ 15: 74 ● chips, €0 otherwise
19		A ○ ○ B	€ 15: 77 ● chips, €0 otherwise
20		A ○ ○ B	€ 15: 80 ● chips, €0 otherwise

Let us describe choice number 6, see line 6 in Fig. 2, as an example. Let us first look at the left hand side (Option A): Option A is always Urn U2. Your selected color (in the example it is green) will be visually displayed behind the winning amount of €15. The other color, yellow, is visually displayed behind the amount of €0. Now let's look at the right hand side (Option B): Option B for choice (row) number 6 is Urn K2 and it states that 38 chips out of the total amount of 100 chips are of your selected color (in the example it is green). The remaining chips, 62, are thus yellow.

If part 2 of task 1 is randomly chosen at the end of the experiment as the one that determines your payoff, your payment will be determined as follows. The computer will randomly select with equal chances one of the 20 choices. If the computer, for instance, selects choice (row) number 6 from this task to be played for real in order to determine your earnings at the end of this experiment, we will let you draw a chip from the urn that you indicated to prefer in that row:

- If you have chosen option A, you may draw one chip from urn U2. Remember this is the urn produced at the beginning of the experiment. If the color you draw corresponds to your selected color, you win €15. If you draw the other color, you win nothing.
- If you have chosen option B, we will create a see-through urn with as many chips in your selected color as indicated in that row. For example, in row 6 (choice 6) we would put 38 chips of your selected color (green) into the urn and 62 chips of the other color. You may then draw one chip from this urn without looking. If you draw a chip corresponding to your selected color, you win €15, and nothing if you draw a chip in the other color.

In this part 2 of task 1 you will have to make 20 decisions like the one described above. Each time you will be asked to indicate your preference for drawing a chip from urn U2 (option A) or urn K2 (option B).

Quiz

To make sure that everything is clear to you, you may answers the questions below. These answers are **not** related at all to the earnings you can win in this experiment. If you have completed all questions you can raise your hand and an experimenter will come to check your answers. If anything is unclear, you may also raise your hand.
Please take your time to fill in the questions. You may start making decisions in Task 1 once all participants are ready.

Please indicate whether the statements below are true or false:

1. I will be informed about the exact content of urn K2 throughout task 1

   True / False

2. In Part 2, Urn K2 is always composed of 50 green and 50 yellow chips

   True / False

3. I have selected a color at the start of the experiment

   True / False

4. What is the minimum amount of colors in urn U2?

   Minimum ____ different colors

5. How many chips do both urns contain?

   ___ balls

6. What is the probability that you will draw a chip in your selected color if urn K2 has a composition as shown in choice number 7 in Fig 2?

   ____% chance of winning

7. Do you know the probability that you will draw a chip in your selected color from urn U2?

   Yes / No

8. The content of urn U2 changes between the decisions I need to make

   True / False

TASK 2

In this task you will again make several decisions between two different urns each filled with 100 chips. Let us first inform you about the urns in task 2.

Urns

In this task there are two urns, named 'urn K10' and 'urn U10'. Urn K10 and urn U10 are each filled with 100 chips. There are 10 possible colors: black, green, grey, red, light green, blue, orange, purple, pink and yellow chips.

- Urn K10 has a fixed composition of 10 colors which will be described to you below.
- Urn U10 is the urn that was produced at the beginning of the experiment and it has an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips.

Your decisions

Part 1

In part 1 of this task you have to choose between a draw from urn U10, which we produced at the beginning of the experiment, and urn K10. Remember, that both urns have 100 chips that can either have a red, yellow, grey, green, blue, purple, pink, orange, light green or black color. In urn U10 you do not know how many chips are of each of the ten possible colors. In part 1 of this task urn K10 has exactly 10 red, 10 yellow, 10 grey, 10 green, 10 blue, 10 purple, 10 pink, 10 orange, 10 light green and 10 black chips, so 10 chips of each color. In the following we again assume, but only for illustration purposes, that you have selected the color green at the beginning of the experiment. In part 1 of this task you simply have to choose once from which of the two urns you would like to draw a chip: from urn U10 (Option A) or from urn K10 (Option B).

If part 1 of this task is selected at the end of the experiment to determine your payoff, you can draw a chip (without looking) from the urn you have chosen. If the drawn chip has the color you selected at the beginning of the experiment, you will win €15. If the drawn chip has the other color, you win nothing (€0).

Part 2
After your decision in part 1, you will make several choices in part 2 of this task where you will again decide if you wish to draw a chip from Urn U10 or Urn K10. We again assume here for illustration purposes that you had selected green at the beginning of the experiment. You will have to make 20 choices which are all displayed on one screen. In every choice you will have to decide between Option A: Urn U10 and Option B: Urn K10. Urn U10 is the urn produced at the beginning of the experiment. Just as a reminder, Urn U10 has 100 chips in an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green or black chips. Urn K10 also has 100 chips, but in a composition you will know. For every choice you will be informed how many of the 100 chips in urn K10 have the color you selected at the beginning of the experiment. The remaining marbles are then a combination of the remaining 9 colors.

If part 2 of task 2 is randomly chosen at the end of the experiment as the one that determines your payoff, your payment will be determined as follows. The computer will randomly select with equal chances one of the 20 choices. If the computer, for instance, selects the following choice (row) to be played for real in order to determine your earnings; a choice between Option A (urn U10) and Option B (urn K10) which gives you information that 15 chips in Urn K10 are of your selected color. We will let you draw a chip from the urn that you indicated to prefer in that row:

- If you have chosen option A, you may draw one chip from urn U10. Remember this is the urn produced at the beginning of the experiment. If the color you draw corresponds to your selected color, you win €15. If you draw the other color, you win nothing.
- If you have chosen option B, we will create a see-through urn with as many chips in your selected color as indicated in that row. In this example, we would put 15 chips of your selected color (green) into the urn and 85 chips of the other nine colors. You may then draw one

- chip from this urn without looking. If you draw a chip corresponding to your selected color, you win €15, and nothing if you draw a chip in the other color.

In this part 2 of task 2 you will have to make 20 decisions like the one described above. Each time you will be asked to indicate your preference for drawing a chip from urn U10 (option A) or urn K10 (option B).

Quiz

To make sure that everything is clear for you, you may answers the questions below. If you have completed all questions you can raise your hand and an experimenter will come to check your answers. If anything is unclear, you may also raise your hand.
Please take your time to fill in the questions. We will continue with Task 2 once all participants are ready.

Please indicate whether the statements below are true or false:

1. The content of Urn K10 changes throughout part 2 of this task

True / False

2. In part 1 of this task, Urn K10 is composed of 50 green and 50 yellow chips

True / False

3. Is green the selected color for all participants

True / False

4. Is urn U10 composed of all 10 colors

True / False

5. What is the probability that you will draw a chip in your selected color from urn K10 in Part 1?

   ____% chance of winning

6. How many balls do both urns contain?
   Both urns contain ___ balls

7. What is the probability that you will draw a chip in your selected color if urn K10 has a composition of 30 marbles in your selected color?
   ____% chance of winning

8. Do you know the probability that you will draw a chip in your selected color from urn U10?
   Yes / No

TASK 3

In this task you will make again several decisions between two different urns each filled with 100 chips. Let us first inform you about the urns in task 3.

Urns
In this task there are two urns, named 'urn K10' and 'urn U10'. These urns are the exact same urns from the previous task! As a reminder, urn K10 and urn U10 are each filled with 100 chips. There are 10 possible colors: black, green, grey, red, light green, blue, orange, purple, pink and yellow.

- Urn K has a fixed composition of 10 colors, which will be described to you below.
- Urn U has an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips. It is the exact same urn from the last task! It was produced at the beginning of the experiment.

Selected colors

In the beginning of the experiment you selected one color; either green or yellow. Let us assume, only for illustration purposes, that you chose green. The other nine colors are then: black, grey, red, light green, blue, orange, purple, pink and yellow. In this task these are then your **nine selected colors.**

Part 1

In part 1 of this task you have to choose between a draw from urn U10, which we produced at the beginning of the experiment, and urn K10. Remember, that both urns have 100 chips that can either have red, yellow, grey, green, blue, purple, pink, orange, light green or black chips. In urn U10 you do not know how many chips are of each of the ten possible colors. In part 1 of this task urn K10 has exactly 10 red, 10 yellow, 10 grey, 10 green, 10 blue, 10 purple, 10 pink, 10 orange, 10 light green and 10 black chips, so 10 chips of each color. In the following we again assume, but only for illustration purposes, that you have selected the color green at the beginning of the experiment and thus that black, grey, red, light green, blue, orange, purple, pink and yellow are your nine selected chips. In part 1 of this task you simply have to choose from which urn you would like to draw a chip: from urn U10 (Option A) or from urn K10 (Option B).

If part 1 of this task is selected at the end of the experiment to determine your payoff, you can draw a chip (without looking) from the urn you have chosen. If the drawn chip has any of your **nine selected colors**, you will win €15. If the drawn chip has the other color, you win nothing (€0).

Part 2

After your decision in part 1, you will make several choices in part 2 of this task where you will again decide if you wish to draw a chip from Urn U10 or Urn K10. We again assume here for illustration purposes that you had selected green at the beginning of the experiment. **Also for this part it means that the other nine colors are your selected colors for task 3, part 2: black, grey, red, light green, blue, orange, purple, pink and yellow.** You will have to make 20 choices which are all displayed on one screen. In every choice you will have to decide between Urn U10 and Urn K10. Urn U10 is the urn produced at the beginning of the experiment. Just as a reminder, Urn U10 has 100 chips in an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green or black chips. Urn K10 also has 100 chips, but in a composition you will know. For every choice you will be informed how many of the 100 chips are of your nine selected colors. The remaining marbles are then green (or yellow depending on the color you selected at the beginning of the experiment).

If part 2 of task 2 is randomly chosen at the end of the experiment as the one that determines your payoff, your payment will be determined as follows. The computer will randomly select with equal chances one of the 20 choices. If the computer, for instance, selects the following choice (row) to be played for real in order to determine your earnings; a choice between Option A (urn U10) and Option B (urn K10) which gives you information that 75 chips in Urn K10 are of your nine selected colors. We will let you draw a chip from the urn that you indicated to prefer in that row:

- If you have chosen option A, you may draw one chip from urn U10. Remember this is the urn produced at the beginning of the experiment. If the color you draw corresponds to one of your nine selected colors, you win €15. If you draw the other color, you win nothing.
- If you have chosen option B, we will create a see-through urn with as many chips in your nine selected color as indicated in that row. In this example, we would put 75 chips of your nine selected color into the urn and 15 chips of the remaining color (in this example thus green). You may then draw one chip from this urn without looking. If you draw a chip corresponding to one of your nine selected colors, you win €15, and nothing if you draw a chip in the remaining color.

In this part 2 of task 3 you will have to make 20 decisions like the one described above. Each time you will be asked to indicate your preference for drawing a chip from urn U10 (option A) or urn K10 (option B).

Quiz

To make sure that everything is clear for you, you may answers the questions below. If you have completed all questions you can raise your hand and an experimenter will come to check your answers. If anything is unclear, you may also raise your hand.
Please take your time to fill in the questions. We will continue with Task 3 once all participants are ready.
Please indicate whether the statements below are true or false:

1. The content of <u>Urn U10</u> is the same as from Task 2

   True / False

2. In Task 3 there are nine selected colors

   True / False

3. If <u>Urn K10</u> is composed as in part 1 of this task, I have 90% chance to draw a chip corresponding to one of my nine selected colors
   True / False

4. I also have a 90% chance to draw a chip corresponding to one of my nine selected colors for <u>urn U10</u>

   True / False

5. How many balls do both urns contain?
   Both urns contain ___ balls

6. What is the probability that you will draw a chip in your selected color if <u>urn K10 has a composition of 70 marbles in your nine selected color</u>?
   ____% chance of winning

7. **7.** Do you know the probability that you will draw a chip in your selected color from urn U10?
   Yes/No

Task 4

In this last task, an urn is filled with 10 balls**: 5 yellow balls and 5 green balls.** Please indicate for each row if you prefer receiving the certain amount of money at that row, or you choose to draw a ball. If one of your choices from task 4 gets selected to determine your earnings, you may either draw a ball if you chose Option B or you receive the sure amount if you chose Option A. If you choose to draw a ball, you may randomly select a marble from a bowl filled with exactly 5 yellow and 5 green marbles, and the color of the selected ball will determine your earnings. If the color of the marble is similar to your selected color at the beginning of the experiment, you win €15, else nothing. You will be asked to enter your decision at the computer screen.

	Option A	Option B
1	O I choose the certain amount of € 0.75	O I choose to draw a ball
2	O I choose the certain amount of € 1.50	O I choose to draw a ball
3	O I choose the certain amount of € 2.25	O I choose to draw a ball
4	O I choose the certain amount of € 3.00	O I choose to draw a ball
5	O I choose the certain amount of € 3.75	O I choose to draw a ball
6	O I choose the certain amount of € 4.50	O I choose to draw a ball
7	O I choose the certain amount of € 5.25	O I choose to draw a ball
8	O I choose the certain amount of € 6.00	O I choose to draw a ball
9	O I choose the certain amount of € 6.75	O I choose to draw a ball
10	O I choose the certain amount of € 7.50	O I choose to draw a ball
11	O I choose the certain amount of € 8.25	O I choose to draw a ball
12	O I choose the certain amount of € 9.00	O I choose to draw a ball
13	O I choose the certain amount of € 9.75	O I choose to draw a ball
14	O I choose the certain amount of € 10.50	O I choose to draw a ball
15	O I choose the certain amount of € 11.25	O I choose to draw a ball
16	O I choose the certain amount of € 12.00	O I choose to draw a ball
17	O I choose the certain amount of € 12.75	O I choose to draw a ball
18	O I choose the certain amount of € 13.50	O I choose to draw a ball
19	O I choose the certain amount of € 14.25	O I choose to draw a ball
20	O I choose the certain amount of € 15.00	O I choose to draw a ball

Section 3

Questionnaire

Part 1

1. Suppose you had €100 in a savings account and the interest rate was 2% per year. After 5 years how much do you think you would have in the account if you left the money to grow?
2. Imagine that the interest rate on your savings account was 1% per year and the inflation was 2% per year. After 1 year, would you be able to buy more than, exactly the same, or less than today with the money in this account?
3. Please tell us whether this statement is true or false. Buying a single company stock usually provides a safer return than a stock mutual fund.
4. Are you familiar with the 'Dienst Uitvoerbaar Onderwijs' (DUO) (Dutch agency responsible for student loans)?
5. Are you aware of the possibility to obtain a loan from DUO?
6. If yes: do you borrow from DUO (excluding allowance for public transport and student finance)?
7. If yes: how much do you borrow per month from DUO?
8. Do you sometimes (not on a monthly basis) borrow an amount (more than €50) for one these reasons: to save, for clothing, to buy certain products, for travelling, other activities; I do not borrow.
9. Do you (also) borrow money from other sources (bank, family, friends etc.)?
10. What is your total monthly income (including salary, student allowance, parents)? Note: this is anything but EXCEPT your potential LOAN.
11. How much do you save each month?
12. After obtaining your degree, what amount of student debt do you think you will have?
13. What are your living expenses?
14. A bat and a ball cost $1.10 in total. The bat costs $1 more than the ball costs. How much does the ball cost?

15. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
16. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, long would it take for the patch to cover half of the lake?

Part 2

1. What is your age?
2. What is your gender?
3. Were you born in the Netherlands?
4. If not, where were you born?
5. What is your nationality?
6. What is your mother tongue?
7. How many brothers do you have?
8. How many sisters do you have?
9. What is your rank amongst your siblings?
10. Which topic do you study?
11. For how many years have you been studying now?
12. Do you live with your parents, or by yourself?

Part 3

1. In uncertain times, I usually expect the best.
2. It's easy for me to relax.
3. If something can go wrong for me, it will.
4. I always look on the bright side of things.
5. I'm always optimistic about my future.
6. I enjoy my friends a lot.
7. It's important for me to keep busy.
8. I hardly ever expect things to go my way.
9. Things never work out the way I want them to.
10. I don't get upset too easily.
11. I'm a believer in the idea that 'every cloud has a silver lining'.
12. I rarely count on good things happening to me.

4)
Appendix – The uncertain adolescent

These experimental instructions are in Dutch. On request English version can be obtained.

Inleiding

Welkom bij ons experiment. Het totale experiment bevat vijf verschillende onderdelen. In 3 onderdelen ga je keuzes maken en de laatste 2 onderdelen zijn vragenlijsten. Per onderdeel volgt een aparte uitleg. Als je vragen hebt of als er iets onduidelijk is, steek dan je hand op en dan komen we langs om je te helpen.

Voordat we beginnen met de eerste taak van dit experiment zullen we eerst wat organisatorische regels uitleggen. Praat vanaf nu asjeblieft niet meer met je buurman of buurvrouw. Je kunt geld verdienen met dit experiment, dus luister aandachtig zodat de spelregels duidelijk worden. Voor je medewerking in dit experiment ontvang je een deelname-bedrag van €3. Naast dit deelname-bedrag kun je nog een bonus winnen. De hoogte van deze bonus hangt af van de keuzes die je in de 3 keuzeonderdelen van dit experiment maakt. Het geld dat je wint wordt na jullie laatste lesuur in contante uitbetaald. Tijdens de uitleg zullen we herhaaldelijk even stoppen om jullie de gelegenheid te geven om vragen te stellen. Mocht je een vraag hebben, of iets onduidelijk vinden, steek dan gerust je hand op.

Vanochtend hebben wij willekeurig een van de 3 keuzeonderdelen van dit experiment geselecteerd. In die specifieke taak is vervolgens 1 keuze willekeurig geselecteerd. Deze keuze zal voor alle leerlingen gelden en wordt aan het einde van deze schooldag uitgespeeld. De beslissing die jijzelf maakt voor de geselecteerde keuze bepaalt de hoogte van je bonus. In de afzonderlijke taken die we met jullie gaan doornemen, staat precies uitgelegd hoe en wat de hoogte is van de bonus (in het geval een keuze uit die taak de bonus zal bepalen).
Alles duidelijk tot nu doe? *(tijd om vragen te beantwoorden)*

Taak 1

Deel 1

Taak 1 van dit experiment bestaat uit twee delen. In totaal moet je 40 beslissingen maken, 20 in het eerste deel en 20 in het tweede deel. We zullen nu eerst het eerste deel uitleggen. In dit deel moet je 20 keer kiezen tussen het ontvangen van een zekere uitkomst óf het trekken van een pingpongbal uit zak A. Bij het trekken van een pingpongbal uit deze zak A kun je € 5 winnen of niets. Slechts één van deze beslissingen is relevant voor het eventueel ontvangen van een bonus. Welke beslissing dit is zullen we uitleggen aan het einde van de instructie van deel 1. We leggen nu uit hoe het trekken van de pingpongbal uit zak A in zijn werk gaat. Als eerste wordt deze zak gevuld met 10 witte en 10 oranje pingpongballen. *(vul de zak waarbij de pingpongballen expliciet geteld worden)*. Als je in de relevante beslissing ervoor gekozen hebt om een bal te trekken uit zak A pak je blindelings een pingpongbal uit deze zak. Voordat je een pingpongbal pakt mag je zelf een kleur kiezen (bijvoorbeeld de kleur oranje). Als de getrokken bal overeenkomt met jouw gekozen kleur ontvang je € 5. Als de kleur van de pingpongbal niet overeenkomt met jouw geselecteerde kleur, dan ontvang je niets.

Je ontvangt een keuzeformulier dat eruit ziet als de slide op de beamer. *(Zet beamer aan en wijs erna*). Wanneer je het spel speelt zullen we je vragen om bij iedere regel een keuze te maken tussen het trekken van een pingpongbal uit zak A *(wijs naar links)* of het ontvangen van een gegarandeerd bedrag *(wijs naar rechts)*. Dit ziet er als volgt uit: in de eerste regel kies je of je liever een pingpongbal uit zak A wilt trekken en kans maakt om € 5 te winnen of dat je liever het gegarandeerde bedrag van € 0.25 wilt ontvangen. Stel dat je liever een pingpongbal uit zak A wilt trekken dan het gegarandeerde bedrag wilt ontvangen, welke van de twee rondjes moet je dan aankruisen? Juist, dan kruis je het rondje aan de linker kant aan.

In de tweede rij moet je weer kiezen tussen het trekken van een pingpongbal uit zak A of het ontvangen van een zeker bedrag. Nu kun je er echter voor kiezen om € 0.50 als gegarandeerd bedrag te ontvangen. Zoals je kunt zien neem het bedrag dat aan de rechter zijde staat steeds toe. Zo lang je liever een pingpongbal trekt uit zak A dan dat je dit vaste bedrag wilt ontvangen kruis je het rondje aan de linker kant aan.

Nu leggen we uit hoe de uitbetaling in zijn werk gaat. Als deel 1 van taak 1 was geselecteerd als de taak die de individuele bonus zal bepalen, was vervolgens een van de 20 rijen willekeurig geselecteerd. Vervolgens zal deze geselecteerde rij voor alle leerlingen de hoogte van de bonus bepalen. De keuze die ieder apart in deze rij heeft gemaakt, bepaalt de exacte hoogte van de bonus. Bijvoorbeeld, stel dat rij nummer 10 willekeurig is geselecteerd (wijs aan op beamer), dan mag je eerst een kleur selecteren en vervolgens een pingpongbal uit zak A trekken wanneer jijzelf het linker bolletje had gevinkt. Je wint dan dus € 5 als de pingpongbal overeenkomt met jouw geselecteerde keuze, en niets wanneer dit niet het geval is. Als je voor rij 10 het rechter bolletje had aangevinkt, dan ontvang je € 2.50.

Maak nu je keuzes in keuzeformulier 1.A.

Keuzeformulier 1.A

[1] trek een bal uit zak A	O	of	O	0.25 euro zeker weten
[2] trek een bal uit zak A	O	of	O	0.50 euro zeker weten
[3] trek een bal uit zak A	O	of	O	0.75 euro zeker weten
[4] trek een bal uit zak A	O	of	O	1 euro zeker weten
[5] trek een bal uit zak A	O	of	O	1.25 euro zeker weten
[6] trek een bal uit zak A	O	of	O	1.50 euro zeker weten
[7] trek een bal uit zak A	O	of	O	1.75 euro zeker weten
[8] trek een bal uit zak A	O	of	O	2 euro zeker weten
[9] trek een bal uit zak A	O	of	O	2.25 euro zeker weten
[10] trek een bal uit zak A	O	of	O	2.50 euro zeker weten
[11] trek een bal uit zak A	O	of	O	2.75 euro zeker weten
[12] trek een bal uit zak A	O	of	O	3 euro zeker weten
[13] trek een bal uit zak A	O	of	O	3.25 euro zeker weten
[14] trek een bal uit zak A	O	of	O	3.50 euro zeker weten
[15] trek een bal uit zak A	O	of	O	3.75 euro zeker weten
[16] trek een bal uit zak A	O	of	O	4 euro zeker weten
[17] trek een bal uit zak A	O	of	O	4.25 euro zeker weten
[18] trek een bal uit zak A	O	of	O	4.50 euro zeker weten
[19] trek een bal uit zak A	O	of	O	4.75 euro zeker weten
[20] trek een bal uit zak A	O	of	O	5 euro zeker weten

Deel 2

Nu leggen we het tweede gedeelte van taak 1 uit. Het tweede gedeelte is vergelijkbaar met het eerste gedeelte. Het enige verschil is dat zak A wordt vervangen door zak B. Nu moet je kiezen tussen het trekken van een pingpongbal uit zak B en misschien € 5 winnen of het ontvangen van een gegarandeerd bedrag.

Het trekken van een bal uit zak B werkt als volgt: deze zak bevat ook 20 pingpongballen. Deze pingpongballen zijn wit of oranje, maar deze keer vertellen we je niet wat het exacte aantal witte en oranje pingpongballen in zak B zijn. In totaal zijn er 20 pingpongballen in zak B. Als je ervoor kiest om een pingpongbal uit zak B te trekken, dan mag je blindelings een pingpongbal uit zak B graaien. Voordat je deze pingpongbal trekt, mag je eerst een kleur kiezen. Als de pingpongbal die jij zelf uit zak B trekt overeenkomt met jouw gekozen kleur, dan ontvang je € 5. Als de kleur van de pingpongbal niet overeenkomt met jouw gekozen kleur, dan ontvang je niets.

Je ontvangt een keuzeformulier dat overeenkomt met het voorbeeld op de slide op de beamer. *(Zet beamer aan en wijs erna*). We vragen je om ook bij dit formulier een keuze te maken voor iedere rij. Nu moet je ervoor kiezen om een pingpongbal uit zak B te trekken *(wijs naar links)* of een zeker bedrag te ontvangen *(wijs naar rechts)*. Dit ziet er als volgt uit: in de eerste regel kies je of je liever een pingpongbal uit zak B wilt trekken en kans maakt om € 5 te winnen of dat je liever € 0.25 zeker weten ontvangt. Stel dat je liever een pingpongbal uit zak B trekt dan dat je het gegarandeerde bedrag ontvangt, welke van de twee rondjes moet je dan aankruisen? Juist, dan kruis je het rondje aan de linkerkant aan.

In de tweede rij moet je weer kiezen tussen het trekken van een pingpongbal uit zak B of een gegarandeerd bedrag. Nu kun je er echter voor kiezen om € 0.50 gegarandeerd te ontvangen. Zoals je kunt zien neem het bedrag dat aan de rechter zijde staat steeds toe. Zo lang je liever een pingpongbal uit zak B wilt trekken dan dat je het vaste bedrag wilt ontvangen, kruis je het rondje aan de linker kant aan.

Nu leggen we uit hoe de uitbetaling in zijn werk gaat. Als deel 2 van taak 1 was geselecteerd als de taak die de individuele bonus zal bepalen, is vervolgens een van de 20 rijen willekeurig geselecteerd. Vervolgens zal deze geselecteerde rij voor alle leerlingen de hoogte van de bonus bepalen. De keuze die ieder apart heeft gemaakt in deze geselecteerde rij, bepaalt de exacte hoogte van de bonus. Bijvoorbeeld, stel dat rij nummer 15 willekeurig is geselecteerd (wijs aan op beamer), dan mag je eerst een kleur selecteren en vervolgens een pingpongbal uit zak B trekken wanneer jijzelf het linker bolletje had gevinkt. Je wint dan dus € 5 als de pingpongbal overeenkomt met jouw geselecteerde keuze, en niets wanneer dit niet het geval is. Als je voor rij 15 het rechter bolletje had aangevinkt, dan ontvang je € 3.75.

Keuzeformulier 1.B

[1] trek een bal uit zak B	O	of	O	0.25 euro zeker weten
[2] trek een bal uit zak B	O	of	O	0.50 euro zeker weten
[3] trek een bal uit zak B	O	of	O	0.75 euro zeker weten
[4] trek een bal uit zak B	O	of	O	1 euro zeker weten
[5] trek een bal uit zak B	O	of	O	1.25 euro zeker weten
[6] trek een bal uit zak B	O	of	O	1.50 euro zeker weten
[7] trek een bal uit zak B	O	of	O	1.75 euro zeker weten
[8] trek een bal uit zak B	O	of	O	2 euro zeker weten
[9] trek een bal uit zak B	O	of	O	2.25 euro zeker weten
[10] trek een bal uit zak B	O	of	O	2.50 euro zeker weten
[11] trek een bal uit zak B	O	of	O	2.75 euro zeker weten
[12] trek een bal uit zak B	O	of	O	3 euro zeker weten
[13] trek een bal uit zak B	O	of	O	3.25 euro zeker weten
[14] trek een bal uit zak B	O	of	O	3.50 euro zeker weten
[15] trek een bal uit zak B	O	of	O	3.75 euro zeker weten
[16] trek een bal uit zak B	O	of	O	4 euro zeker weten
[17] trek een bal uit zak B	O	of	O	4.25 euro zeker weten
[18] trek een bal uit zak B	O	of	O	4.50 euro zeker weten
[19] trek een bal uit zak B	O	of	O	4.75 euro zeker weten
[20] trek een bal uit zak B	O	of	O	5 euro zeker weten

Zak B

Wanneer een van de rijen uit deel 2 wordt geselecteerd en je hebt aangegeven dat je voor die rij een pingpongbal uit zak B wilt trekken, mag je zelf de kleur kiezen – wit of oranje – die zal bepalen of de getrokken pingpongbal tot een bonus leidt.

Graag willen we nu van jou weten wat je denkt dat de compositie van Zak B is?
Hoeveel pingpongballen zijn er in jouw gekozen kleur?

…… pingpongballen in mijn gekozen kleur.

Taak 2

Taak 2 van dit experiment bestaat uit 5 verschillende loterijkeuzes waarbij je elke keer een keuze dient te maken tussen Optie A en Optie B. Elke keuze wordt grafisch op dezelfde manier weergegeven. Laten we keuze 1 als voorbeeld samen doorlopen *(wijs aan op beamer)*.

Optie A in keuze 1 beschrijft een rode dobbelsteen waarbij je € 3 kunt ontvangen als een van de nummers 1, 2 of 3 worden gerold. Worden de overige cijfers 4, 5 of 6 gerold, dan dient er een zwarte dobbelsteen gerold te worden. Je ontvangt € 1 wanneer de zwarte dobbelsteen vervolgens de nummers 1, 2 of 3 rolt en verliest € 1 wanneer 4, 5 of 6 wordt gerold. Bij Optie B daarentegen zul je € 4.50 ontvangen wanneer een van de nummers 1, 2 of 3 worden gerold, en zal er wederom een zwarte dobbelsteen aan te pas komen wanneer bij de rode dobbelsteen 4, 5 of 6 wordt gerold. Je ontvangt vervolgens € 1 wanneer de zwarte dobbelsteen vervolgens de nummers 1, 2 of 3 rolt en verliest € 1 wanneer 4, 5 of 6 wordt gerold.

Bij de overige 4 loterijen gaat het om andere cijfers, maar de afbeelding van de dobbelstenen en de implicaties daarvan zijn identiek.

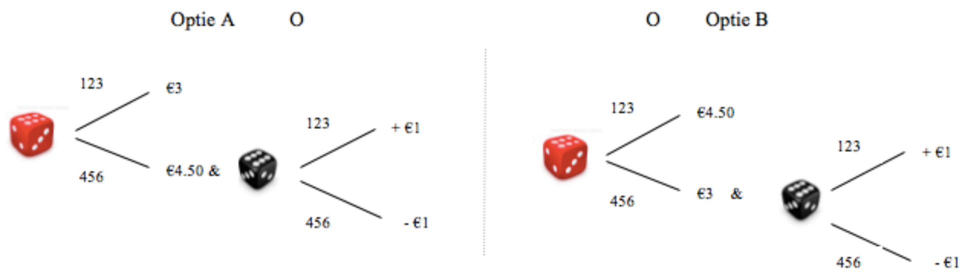
Geef je keuze aan door het rondje bij Optie A of het rondje bij Optie B aan te kruisen.

Nu leggen we uit hoe de uitbetaling in zijn werk gaat. Als taak 2 was geselecteerd als de taak die de individuele bonus zal bepalen, is vervolgens een van de 5 loterijen willekeurig geselecteerd. Stel nu dat loterij 3 willekeurig geselecteerd is, dan zullen we ofwel de loterij behorende bij Optie A uitspelen als je daarvoor gaat kiezen, danwel de loterij van Optie B uitspelen als je daarvoor gaat kiezen. Dit doen we daadwerkelijk aan de hand van een rode en zwarte dobbelsteen die je zelf mag rollen.

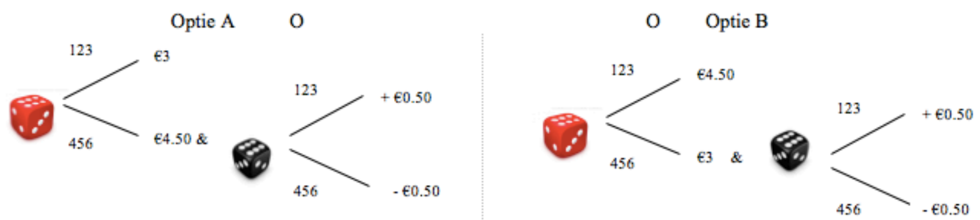
Alles duidelijk? *(tijd om vragen te beantwoorden)*

Keuzeformulier 2

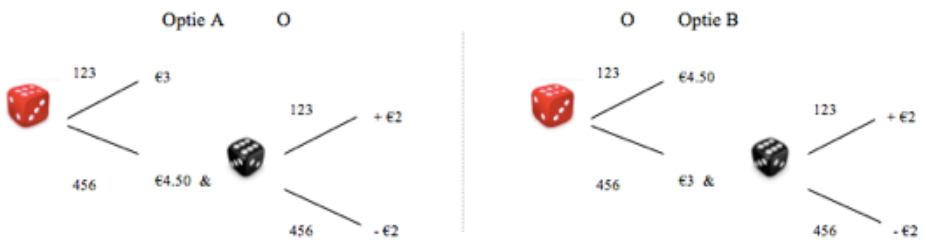
Keuze 1

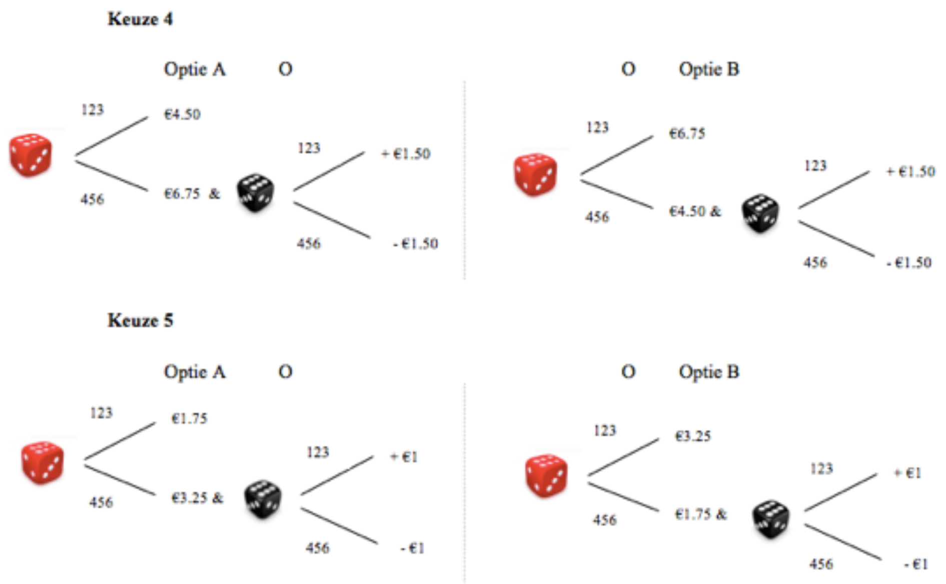


Keuze 2



Keuze 3





Taak 3

Taak 3 van dit experiment bestaat uit 6 verschillende loterijkeuzes waarbij je elke keer een keuze dient te maken tussen Ja en Nee. 'Ja' betekent dat je de loterij wilt spelen en 'nee' houdt in dat je de loterij niet wilt spelen. In dat geval ontvang je niets. Elke keuze wordt hieronder op dezelfde manier weergegeven. Laten we keuze 1 als voorbeeld samen doorlopen.
De loterij bestaat uit een 50% kans om € 2.25 te winnen en een 50% kans om € 0.25 te verliezen. Als je deze loterij graag zou willen spelen, dan kruis je het bolletje bij 'ja' aan. Als je deze loterij niet wilt spelen, dan kruis je 'nee' aan. Bij een keuze van 'nee' is altijd het geval dat je niets ontvangt.

Bij de overige 6 loterijen gaat het om andere cijfers, maar de strekking van de loterijen is hetzelfde.

Nu leggen we uit hoe de uitbetaling in zijn werk gaat. Als taak 3 was geselecteerd als de taak die de individuele bonus zal bepalen, is vervolgens een van de 6 loterijen willekeurig geselecteerd. Stel nu dat loterij 5 willekeurig geselecteerd is, dan zullen we ofwel de loterij uitspelen als je voor ‘ ja’ zou kiezen, of er gebeurt niets in het geval je voor ‘nee’ gaat kiezen. De loterij wordt uitgespeeld met een muntstuk. Je mag hierbij zelf aangeven of je kop of munt wilt verbinden aan het winnende getal.

Keuzeformulier 3

[1] Zou je de volgende loterij willen spelen:
- 50% kans: + € 2.25
- 50% kans: - € 0.25
Ja O of O Nee (€ 0)

[2] Zou je de volgende loterij willen spelen:
- 50% kans: + € 2.25
- 50% kans: - € 0.75
Ja O of O Nee (€ 0)

[3] Zou je de volgende loterij willen spelen:
- 50% kans: + € 2.25
- 50% kans: - € 1.25
Ja O of O Nee (€ 0)

[4] Zou je de volgende loterij willen spelen:
- 50% kans: + € 2.25
- 50% kans: - € 1.75
Ja O of O Nee (€ 0)

[5] Zou je de volgende loterij willen spelen:
- 50% kans: + € 2.25
- 50% kans: - € 2.25
Ja O of O Nee (€ 0)

[6] Zou je de volgende loterij willen spelen:
- 50% kans: + € 2.25
- 50% kans: - € 2.75
Ja O of O Nee (€ 0)

Taak 4

In de vierde taak van dit experiment zul je enkele vragen moeten beantwoorden. Probeer het goede antwoord te geven. Je hebt maximaal 5 minuten de tijd.

Keuzeformulier 4

Een honkbalknuppel en een bal kosten bij elkaar €1.10. De knuppel kost €1.00 meer dan de bal. Hoeveel kost de bal? _________ Cent

Als 5 machines er 5 minuten over te doen om 5 onderdelen te maken, hoe lang hebben 100 machines dan nodig om 100 onderdelen te maken?________ Minuten

In een meer drijft een groep leliebladeren rond. Iedere dag wordt deze groep twee keer zo groot. Als de bladeren er 48 dagen over doen om het gehele meer te beslaan, hoe lang duurt het dan voordat de helft van het meer is bedekt?

List of Figures

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Nederlandse samenvatting (Dutch summary)

In ons dagelijks leven worden we geconfronteerd met vele keuzes waarvan we niet precies weten wat de uitkomst zal zijn. Economen maken onderscheid tussen twee typen onzekerheid: risico en ambiguïteit. We spreken van risico als we weten met hoeveel kans een bepaalde uitkomst zal plaatsvinden. Een welbekende situatie dat wordt gekenmerkt door risico is bijvoorbeeld het weer. Je staat op het punt om te gaan fietsen en kijkt nog even op je weer applicatie om te verifiëren dat de komende uren de kans op regen laag is, bijvoorbeeld maar 10 procent. Een ander bekend voorbeeld van risico is het gooien van een muntstuk waarvan je evenveel kans hebt op kop of munt. Echter, vele keuzes waarmee we worden geconfronteerd, kunnen niet in precieze kansen uitgedrukt worden. Je weet niet wat de kans is dat je vandaag op de racefiets ten val zal komen. Je weet niet wat de kans is dat je favoriete sportteam hun aankomende wedstrijd zal winnen. Aan deze situaties kunnen we geen objectieve kansen toeschrijven, maar maken we gebruik van onze verwachtingen, ook wel subjectieve kansen genoemd. Standaard economische modellen (zie BOX 2 in de introductie) veronderstellen dat mensen geen voorkeur hebben tussen risico en onzekerheid wanneer de objectieve kans in lijn ligt met een subjectieve kans. Bijvoorbeeld, je verwacht dat Dafne Schippers met 50 procent kans tijdens de Olympische Spelen volgend jaar in Rio de 100m zal winnen. Je weet dit uiteraard niet zeker en daarom spreken we ook wel van een subjectieve kans. Nu leg ik je het volgende kansspel voor: je wint 10 Euro als Dafne Schippers inderdaad goud wint (een subjectieve kans die je met 50% waarschijnlijk acht), of je gooit liever een muntstuk en wint 10 Euro als je kop gooit (een objectieve kans van 50%). Volgens rationele economische theorie zou je onverschillig zijn tussen een weddenschap op voorgaande scenarios. In een zeer influentieel experiment (zie BOX 1 in de introductie) liet Daniel Ellsberg (1961) zien dat mensen wel degelijk schuwen voor ambiguïteit, dat wil zeggen dat ze eerder geneigd zijn om keuzes te maken in situaties die uitgedrukt kunnen worden in objectieve kansen dan in onzekere situaties waarvan individuele verwachtingen de leidraad zijn. Dit gedragspatroon wordt omschreven als ambiguïteit aversie.

In dit proefschrift heb ik mezelf twee onderzoeksvragen gesteld die voortbouwen op de inzichten die ik hierboven heb beschreven. Ten eerste heeft het experimentele gedragsonderzoek ten aanzien van risico en ambiguïteit zich voornamelijk gericht op loterij keuzes. Het gooien van een muntstuk of rollen van een dobbelsteen zijn voorbeelden daarvan. Vele van onze keuzes en de onzerkerheid waarmee gerelateerde uitkomsten plaatsvinden, worden juist veroorzaakt door het handelen van een andere persoon. Bijvoorbeeld, je leent geld aan je beste vriend, je investeert geld in een entrepreneur zodat deze een bedrijf kan starten, of je boekt een kamer bij een wildvreemde via airbnb. In al deze situaties is de bron van de onzekerheid gerelateerd aan de acties van een andere persoon. Deze sociale context is vooralsnog nauwelijks aan bod gekomen bij economische onderzoek naar individuele voorkeuren voor risico en ambiguïteit. Ik heb onderzocht of ambiguïteit aversie beïnvloed wordt wanneer risico en onderzekerheid tot stand komen door een loterij (niet-sociale context) danwel door het handelen van een andere persoon (sociale context). Ten tweede heb ik onderzocht hoe gedragsresultaten uit het laboratorium een accurate voorspeller kunnen zijn van keuzes die mensen daadwerkelijk maken in hun dagelijks leven. Oftewel, als ik tijdens mijn gedragsexperimenten kan identificeren welke personen (het meest) schuwen voor ambiguïteit aversie, laten deze zelfde individuen deze aversie ook zien in hun dagelijkse handelen? Er is onderzoek verricht naar de externe validiteit van risico preferenties, maar ambiguïteit aversie wordt vaak niet in ogenschouw genomen bij dergelijke veldstudies. In mijn onderzoek heb ik onder andere bekeken of risico én ambiguïteit aversie van studenten correleren met hun leengedrag. Ook heb ik bekeken of risico en ambiguïteit aversie van jongvolwassenen, die ik testte op hun middelbare school, een voorspeller zijn van hun zelfvertrouwen in de omgang met hun klasgenoten.

Een divers pallet aan onderzoekstechnieken komen in dit proesfschrift aan bod. Dat is deels ingegeven omdat ik ten doel had gesteld om te achterhalen waarom mensen gevoelig zouden zijn voor de context waarin risico en ambiguïteit tot stand komt en wat de implicatie daarvan is op hun handelen in het dagelijks leven. Daartoe heb ik in dit proefschrift gebruik gemaakt van een mix aan gedragsexperimenten, fMRI experimenten (zie BOX 3 in de introductie) en veldexperimenten. De inzet van fMRI experimenten in economie is een relatief jong veld en beoogt om kennis van het brein te relateren aan gedrag.

De resultaten van mijn proefschrift laten zien dat ambiguïteit aversie in een sociale context sterker is vergeleken met een loterij context. Kort door de bocht gezegd, het is erger wanneer je geld verliest aan de roulettetafel, dan wanneer je zakenpartner er met jouw investering vandoor gaat. Er zijn wel grote individuele verschillen en die worden met name veroorzaakt door verschillen in individuele verwachtingen. De invloed van deze context is ook in het brein te achterhalen en deze resultaten geven ons meer inzicht in de onderliggende processen van menselijk handelen ten aanzien van risico en ambiguïteit. Zo leiden individuele verschillen in sociale ambiguïteit aversie naar een breingedeelte, de inferior frontal gyrus, waarvan we onder andere weten dat deze betrokken is bij het interpreteren van situaties die ambigue zijn. Een persoon die dus meer schuwt voor onzekerheid, is meerdere mogelijke interpretaties aan het (her)overwegen in vergelijking tot een persoon die we zouden kunnen omschrijven als meer kordaat.

Daarnaast vind ik dat gedragsresultaten correleren met gedrag buiten het laboratorium. Ik vind, bijvoorbeeld, dat studenten die het meest schuwen voor ambiguïteit ook het minst bereid zijn om geld te lenen tijdens hun studie. Op basis van deze resultaten heb ik suggesties gedaan voor beleidsmaatregelen. Tevens geeft dit proefschrift aanleiding tot verder vervolgonderzoek (zie conclusie) en deze onderzoeksvragen hoop ik in de nabije toekomst te kunnen beantwoorden.

Biography

Kim Fairley was born on June 24, 1985, in Malden, The Netherlands. In 2003 she began her studies in Business Administration at the Radboud University Nijmegen. She obtained her Bachelor Degree in 2006. From 2006-2007 she worked for National student-run organization *Integrand*, which manages internships for academic students in The Netherlands. In September 2007 she worked for half a year for an educational project in a rural village in India. In September 2008 she continued to pursue her academic career by studying Financial Economics at Radboud University for which she first had to do a transition year in which she took basic Economic courses. She obtained her Master Degree in Financial Economics in 2011. She wrote her Master Thesis under the supervision of Dr. Jana Vyrastekova on *Trust under risk and ambiguity*. During her Master thesis she contacted Prof. Alan Sanfey from the Donders Institute for Brain, Cognition and Behaviour which led her to include the biological foundations of trust under uncertainty in her Master's Thesis. Kim's Master Thesis was awarded the Second best Master Thesis written in the class of 2010-2011 from the Department of Management Sciences. Through this path Kim Fairley developed her affinity with and interests towards behavioral economics, experimental economics and neuroeconomics. After completing her Master Thesis she started her PhD trajectory at Financial Economics under the supervision of Prof. Utz Weitzel and Prof. Alan Sanfey. This dissertation is the result of her work at the Department of Economics at Radboud University and the Donders Institute for Brain, Cognition and Behaviour. During her PhD she also assisted Prof. Esther-Mirjam Sent with the translation of insights from behavioral economics and neuroeconomics to policy making. She also taught introductory economics and behavioral economics and supervised students with their Bachelor and Master Thesis. Currently, she is employed as a postdoctoral researcher at the University of Colorado Boulder, Colorado, United States.

Publication list

Published
Fairley, K., Stallen, M., Sent, E.M., 2013. De kracht van sociale normen, Economisch Statistische Berichten 98 (4672S), pp. 27-31

Under review
Fairley, K., Sanfey, A.G., Vyrastekova, J., Weitzel, U., 2014. Trust and risk revisited.

Fairley, K., Weitzel, U. 2015. Ambiguity attitude and borrowing behavior.

Fairley, K., Sanfey, A.G., 2015. The uncertain adolescent. Correlates of social status and preferences for uncertainty in adolescents.

Fairley, K., Sanfey, A.G., Vyrastekova, J., Weitzel, U., 2015. Social sources of risk and uncertainty: an fMRI study.

In preparation
Fairley, K., Sanfey, A.G., Vyrastekova, J., Weitzel, U., 2015. Anticipating rewards. The power of beliefs in activating an expected reward signal in the ventral striatum.

Fairley, K., Weitzel, U. 2015. Producing the Ellsberg urn in different ways: does it matter?